IMPACTS OF PROJECT-BASED SERVICE-LEARNING ON ATTITUDES TOWARDS ENGINEERING IN HIGH SCHOOL AND FIRST-YEAR UNDERGRADUATE STUDENTS

by

MALINDA SCHAEFER ZARSKE

B.A., Saint Mary's College of Maryland, l995

M.A., The Johns Hopkins University, l998

M.S., University of Colorado Boulder, 2002

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written by Malinda Schaefer Zarske
has been approved for the Department of Civil, Environmental, and Architectural Engineering

____
Angela R. Bielefeldt

____
Derek T. Reamon

____
Jacquelyn F. Sullivan

____
R. Scott Summers

____
Fernando L. Rosario-Ortiz

____
Edward W. Wiley

Date_______________

The final copy of this thesis has been examined by the signatories, and we
Find that both the content and the form meet acceptable presentation standards
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Zarske, Malinda Schaefer (Ph.D., Civil, Environmental, and Architectural Engineering)

Impacts of Project-Based Service-Learning on Attitudes towards Engineering in High School and First-Year Undergraduate Students

Thesis directed by Associate Professor Angela R. Bielefeldt

Interest in whether real-world problems or a service learning context increases students' academic performance and intent to find careers in engineering is gaining momentum. The belief that diverse student populations resonate with the idea that *engineers can contribute to improving society* is found throughout the literature, supporting the combination of service-learning with project-based courses as an instructional method that can impact identification with engineering in high school and first-year students, potentially increasing the recruitment and retention of capable and interested learners. While study of these reforms indicates many advantages, little meaningful evidence exists on the psychological and educational benefits from engaging in project-based service-learning.

This thesis examines the evolving identity and attitudes towards community service for both high school and first-year engineering students engaged in project-based design, and whether a service-learning context influences these changing attitudes. Quantitative Likert-style surveys were developed from previously validated instruments and administered to students pre- to post-semester. Each participant was surveyed multiple times during their design experience, and the survey results were aggregated to offer insight into their evolving attitudes towards identity with engineering and service to the community. Using hierarchical linear modeling (HLM) methods, students' responses to survey items were analyzed by comparing students in multiple service and non-service sections of a project-based design course at the high school and first-year engineering levels. Study results indicate that a service-learning context in project-based courses positively impacts identity and attitudes towards community service in targeted underrepresented populations of high school and undergraduate students. A ceiling effect was apparent for some students at both levels, who were predisposed to high community service attitudes and identification with engineering. Based on the results of this study, K-12 and undergraduate should consider project-based service-learning engineering design experiences early and often to improve students' identification with engineering, demonstrate professional and societal relevance of engineering, and potentially increase the interest and retention of a diverse population of students, including women and minorities, into the pipeline of engineering education and engineering workforce.

DEDICATION

This thesis is dedicated to:

John P. and Ruth B. Schaefer

For their love of and commitment to education

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CONTENTS

TABLES

Table

FIGURES

Figure

CHAPTER I

INTRODUCTION

A Call for Improving Engineering Education

Declining graduation rates of U.S. engineering students compared to higher overall college enrollment across the nation, coupled with a high global demand for qualified engineering graduates and greater university accountability, continue to fuel the concerns of the engineering community about the curricula and instruction in engineering institutions (Engineering Trends, 2008; Fortenberry, Sullivan, Jordan, & Knight, 2007; National Science Foundation, 2008). While many Americans are not generally educated adequately in science, technology, engineering and mathematics (STEM) disciplines to contribute to or engage in our increasingly technologically driven society, other countries understand the vital economic dependence on these critical disciplines and are increasing their investment in STEM training and innovation (National Research Council, 2007, 2010). We cannot keep pace with the anticipated future growth of the global science and engineering workforce with only 4.5% of U.S. college graduates majoring in engineering, compared to 21% of college graduates in Asia and 12.5% in Europe (National Academy of Engineering, 2011; National Science Board, 2010a, 2010b).

The National Academies' *Rising Above the Gathering Storm, Revisited* publication (2010), reminds us that amidst a growing population of minority students, we are still not encouraging or attaining a diverse population in STEM undergraduate programs (National Research Council, 2010). U.S. undergraduate enrollment of all racial/ethnic groups is projected to increase (non-Hispanic Caucasians to comprise less than 50% of the college-aged population by 2025), which may be problematic for engineering colleges that have historically struggled to attract these diverse populations into their ranks (American Society for Engineering Education, 2009; Sullivan, 2007; Tienda, 2009; U.S. Census Bureau, 2008).

The overall number of engineering degrees granted in the U.S. has risen in recent years, although not to its historic high of nearly 80,000 in 1985 (National Academy of Engineering, 2011). African Americans and Hispanics comprised ~32% of college-age populations and 23% of college student populations in the U.S. in 2007, and only collectively accounted for 11% of engineering bachelor's degrees awarded in 2009 (American Society for Engineering Education, 2009; Gibbons, 2010). The participation of women in the engineering pipeline has been slowly decreasing from its peak in 1995 at around 21%, now accounting for closer to 18.1% of engineering bachelor's degrees awarded in 2010, up slightly from 17.8% in 2009 (American Society for Engineering Education, 2009; Engineering Trends, 2008; Gibbons, 2010). Since only 4.5% of U.S. BS graduates earn engineering degrees, this means that less than 2% of the nation's engineering BS degrees are awarded to minorities and women annually (National Science Board, 2010a, 2010b). Logic tells us that as our society is becoming more technology-driven, the representation of women and minorities interested in contributing to the technological revolution is shrinking. Yet for U.S. engineering to be globally competitive and remain sensitive to the needs of a changing society, the demographics of undergraduate engineering students must become more representative of the nation's population.

Today's college-aged students are less inclined to choose STEM futures; however, our nation's need for science and engineering innovation has never been more critical. National priority for a stronger STEM education focus at the K-12 level is the goal of the *Engineering Education for Innovation Act*, a bill passed by the U.S. Congress in February 2010 (111th

Congress, 2010). This Act sets aside significant funds for state educational agencies to finance efforts to integrate engineering education into K-12 instruction and curricula. Unfortunately, research reveals that K-12 students are not considering math and science as professionally relevant—closing off future career pathways as early as third grade (Turner & Lapan, 2005). In fact, the proportion of U.S. high school students who choose to obtain science and engineering degrees in college continues at a lower number than in many other countries (National Research Council, 2009). This lack of interest in STEM disciplines is particularly apparent among disadvantaged groups who have been historically underrepresented in those fields (National Research Council, 2007, 2010).

In short, the numbers of qualified and creative engineering graduates must be boosted through increased interest and preparation of college-age students and higher retention rates for engineering undergraduates, which may be realized via improved instructional methods and curricula. Undergraduate engineering has become a test bed for pedagogical interventions to increase student interest and abilities, reflecting the progress of cognitive development research in social science and psychology. Methods such as active-learning, problem-based learning, project-based learning, and service-learning are starting to appear in many engineering course sequences, though not consistently. Unfortunately, the literature does not offer many strongly-designed research studies comparing similar outcomes from different instructional methods at either the K-12 or undergraduate level. More work is needed to determine if and for whom these varying methods are effective, and ultimately, to establish engineering education best practices for our students.

Scope of the Study

The overarching motivation of this research project is to address the gap between the learning styles of today's engineering students and the instructional methods used in engineering education. A review of learning theory from cognitive science, coupled with contemporary teaching strategies discussed in the engineering education literature, offers a variety of curricular interventions to increase competence in learning discipline-specific subject matter. However, inconsistent accounts of useful pedagogy and quality assessment methodologies remain. The primary research focus of this project is on improving K-12 and first-year undergraduate student engineering design experiences through an understanding of the specific psychological and educational benefits of engaging in academic project-based service-learning (PBSL)— an instructional method that actively engages the learner in complex design problems that benefit authentic communities or clients. For this study, the PBSL projects were selected to provide students with engineering design work that results in improved quality of life or higher standard of living for targeted local Colorado communities. These PBSL experiences were compared to project-based learning (PBL) experiences to determine the differential benefits, if any, from the addition of a service component to student-led engineering projects. As a result, the findings of this study increase the base of empirical knowledge available to researchers and educators interested in improving engineering education to better prepare today's students to keep pace with technological advances and attract a wider representation of students into the field.

The participants in this study include both high school and first-year engineering students engaged in hands-on project-based design courses during one academic year. Multiple course sections were offered at the high school and undergraduate levels, with some sections focused on PBSL and others on PBL design. Participants were surveyed multiple times during their design experiences, and the survey results were aggregated to offer insight into the evolving attitudes of both high school and first-year engineering undergraduate students towards identity with engineering and service to the community. Specifically, this study reports the change in perception for high school and undergraduate students engaged in a project-based design course and whether service-learning influences these changing attitudes.

Arrangement of the Thesis

This thesis is developed as three separate articles for publication in a peer-reviewed journal in the field of engineering education. The beginning chapters establish the foundation for this work, including a review of the extensive literature in both cognitive science and engineering education, and the study research questions and hypotheses. Chapters IV through VI present discrete journal articles, each with an introduction, conclusion, and figures inserted in the body of the text. These chapters tell their own story with relation to the data and research questions. The thesis concludes with a chapter on overarching inferences from the study and ideas for future work. The appendices contain extended data output for analyses that are considered in the three journal articles, as well as descriptions of models and variables that were not otherwise included.

CHAPTER II

A REVIEW OF THE LITERATURE

The last decade has seen an increase of instructional practices designed to align with current educational research on student learning. Most of the research on how people learn in general and, more specifically, how they learn technical subjects has been done in the context of science and math; however, some of the more generally accepted theories have been recently extended to engineering education. This literature review overviews the most commonly cited theories of learning in engineering education, describes several instructional techniques based on cognitive research, discusses identity theory with relation to engineering, extends the theories and instructional techniques to both undergraduate and K-12 engineering settings, and talks about persistence and quality assessment.

Learning Theories

The most traditional approach to teaching and learning assumes that knowledge exists independently of an individual, where teaching focuses on the *delivery of the material* over the intellect of the learner and maintains that a structured presentation of facts will create the optimal learning environment (Wankat & Oreovicz, 1993). In other words, if a student is paying attention, she will learn the material if it is presented in an organized way. Engineering and science are traditionally taught using this deductive approach: instructors present material in lecture form and use the principles to illustrate mathematical models. Next, students practice the applications in homework, and finally instructors test the students on their ability to solve similar mathematical problems on exams (Prince, 2006). The main, if any, motivating factors for students are their grades and the notion that the material will become important once they are employed in the professional world (Prince, 2006). This deductive method is related to the behaviorist theory of learning.

Behaviorist Theory of Learning

The behaviorist theory of learning is a passive learning approach. Students are "vessels" waiting to be filled, and knowledge comes in the form of external stimuli. American psychologist and behaviorist B.F. Skinner researched human cognition using a series of reinforcing concepts. He described learning as the result of these stimulus-response associations (Mergel, 1998; Shepard, 2000). The behaviorist model includes several key assumptions: learning occurs by accumulating small pieces of knowledge, learning is hierarchical, tests should be used to demonstrate mastery before moving to the next level of content, and motivation is external and based on positive reinforcement (Shepard, 2000). When designing a content lesson from a behaviorist approach, the teacher starts by setting a goal. Next, individual student tasks are delineated and learning objectives are developed. Assessment is designed to determine whether the criteria for the objectives have been met. The teacher decides what is important for the learner to know and attempts to transfer that knowledge to the learner (Mergel, 1998).

The behaviorist learning theory supports the assignment of a task to all students, breaking the task apart into smaller components, developing related objectives, and measuring student performance based on those objectives (Mergel, 1998). A constructivist model of learning, the second learning theory discussed here, promotes a more active learning experience in which the methods and results of learning may differ for each student.

Piaget's Research in Cognitive Development

Some research in educational psychology argues that people are more strongly motivated to learn when they have a need to know the information (Prince, 2006). Swiss psychologist and epistemologist Jean Piaget researched childhood development and described children's cognitive development as occurring in four distinct stages. His theories of development have been widely used to form the way science is taught in elementary school through college (Gordon, 2009; Wankat & Oreovicz, 1993). Although his description of intellectual development is continuous, the abilities in each stage are distinct from each other and motivated by a person's innate need to function successfully in his world (Wankat & Oreovicz, 1993). To expound, the first stage is the *sensorimotor* period, and in this stage, infants learn by movement and relationship to physical objects. This stage lasts from about birth to two years of age. Towards the end of this stage, young children are able to think about objects that are not within sight. The second stage is called the *preoperational* period. Preoperational thinking describes how children use language to begin to describe the world around them; typically, a child explains her surroundings with very little logic and the explanation is often very concrete and self-centered. Once in the latter part of preoperational thinking, or intuitive phase, the child is able to start to use limited reasoning. However, her conclusions are still often erroneous and irrational, and the child still has little ability to think in a cause and effect context. It is during this time that children begin to classify objects and use numbers to count and organize. Piaget noticed that children around age seven start to move into a *concrete operational* stage. During this stage, a person can do mental operations or logical thought but only using concrete objects. In the concrete operational stage, children can understand basic math concepts while harder formulas can only be accomplished by rote. Logical reasoning is also better understood during this phase. Piaget's last phase of development is *formal operational* or abstract thought. A formal operational thinker often enjoys abstract thought and becomes inventive with her ideas. She can create hypotheses without manipulating a physical object and can generalize from one situation to another. The formal operational thinker can also learn higher mathematics and extend those concepts to solve new problems (Wankat & Oreovicz, 1993).

Piaget noticed that children progress through these stages at different rates, but always follow the same order (Wankat & Oreovicz, 1993). He felt that more important than a child's age is the progression of cognitive development (Lourenço & Machado, 1996). Criticism of Piaget's research includes his restriction to the study of children, ending with adolescents. Critics disparage Piaget for not describing even more advanced learning occurring into adulthood. However, proponents of Piaget's work contend that the structure of the final formal stage is a way of processing information, not limited to the amount of knowledge acquired. In fact, they reference Piaget's writings: after a certain level of cognitive development is reached, then "individual aptitudes become more important" and create "greater differences between subjects (Lourenço & Machado, 1996)." It is estimated that 30-60% of adults fall somewhere in the transition between concrete operational and formal operational thinkers (Wankat & Oreovicz, 1993), meaning these adults use formal operational thought correctly some of the time but not all of the time. For example, engineering education requires some formal operational thought; however, many teens and adults struggle with abstract thought. Engineering students who process in a concrete operational stage can navigate the curriculum by rote learning, partial credit, and doing well in lab. Students who are more familiar with formal operational thinking learn from their mistakes, and use their new knowledge to solve difficult new problems (Wankat & Oreovicz, 1993).

Not only did Piaget study the different intellectual stages of development in children, but he spent extensive time trying to understand the transitional periods between each stage. Piaget theorized that *mental structures* exist into which new information is incorporated. In general, if a new knowledge or experience fits well into the person's existing mental structure, then the data is easily accommodated into the person's knowledge, beliefs, misconceptions, and fears. If the new data does not fit well, then it is transformed until it does fit (Wankat & Oreovicz, 1993). A concrete operational thinker will most likely reject knowledge that does not fit into her existing mental structure. In the case of engineering education, the concrete operational thinker likely memorizes data but never understands it. Transition into formal operation thought occurs when a person has a desire or *motivation* to incorporate or understand the new knowledge (Prince, 2006; Wankat & Oreovicz, 1993). Students must want to learn the material or create a design to move into higher orders of thinking. If new knowledge does not make sense in the existing mental structure, then the person can be thought to be in a state of disequilibrium (Wankat & Oreovicz, 1993).Most organisms have a natural desire to be in a state of equilibrium, and intellectual development is no exception. The desire for equilibrium in intellectual thought is a strong motivator for incorporating new knowledge into an existing mental structure (or rejecting it altogether). Basically, new information must fit within a person's own view of the world to be learned.

Constructivist Theory of Learning

Piaget's research is a forerunner to the *constructivist* theory of learning. A broad definition of constructivism encompasses the construction of knowledge through the integration of individual mental structures combined along with social processes. Constructivism has been traced back as far as 4th -6th century BC, and explains learning as actively influenced by the individual instead of existing independently of the individual, or the behaviorist theory (Prince, 2006; Wankat & Oreovicz, 1993). In other words, knowledge does not simply exist, but is constructed by humans during their interactions with the world around them (Gordon, 2009). In education, the teacher or professor becomes a facilitator of learning instead of a transmitter of knowledge. Students become engaged in developing new knowledge structures by assimilation, and the teacher facilitates the process (Wankat & Oreovicz, 1993). Constructivism encompasses Piaget's *cognitive constructivism* described above, as well as *social constructivism*, or the role of interactions within a social context as the basis for constructing meaning. Overlap exists between the two camps, and it is interesting to note that even some of Piaget's writings suggest that he acknowledges that social factors are necessary for intellectual development (Gordon, 2009; Lourenço & Machado, 1996).

Constructivist research has mostly been conducted in areas other than education, such as psychology and sociology. Limited research has been done on how to connect theory with actual teaching practices (Gordon, 2009). This research suggests that constructivist teaching approaches are successful if new material is presented to students in the context of a familiar, real-world problem and in a manner that requires students to alter their existing mental structures. Also, research implies that successful instruction actually fills in the gaps of knowledge for the students (Prince, 2006). Ideally, students work in small groups, and are engaged in activities that are achievable for their academic level (Prince, 2006). The goal is to wean students away from dependence on instructors as their main source for knowledge acquisition and instead facilitate students into the role of self-learners. Effective constructivist teachers make modifications in their teaching when they find that the students are not learning (Gordon, 2009). Successful constructivist classrooms have a balance of teacher and student-directed learning—both teacher and students are active (not passive) in constructing new knowledge, adopting Piaget's theory that knowledge is essentially a process of inquiry that develops over time (Gordon, 2009).

Situated Learning Theory

The theories supporting situated learning draw from Lave, Wenger, Vygotsky, Dewey, and Greeno (Barab & Plucker, 2002; Vincini, 2003). Situated learning theory centers on the idea that whatever is present in the environment during learning becomes part of what is learned. For example, context and environmental cues can become part of the learning process. When the context changes, such as applying knowledge in the professional realm, the stimuli will be slightly different and the students' response will differ as well. In other words, the learning becomes "situated" in the original learning environment (Svinicki, 2008). Knowing becomes a dynamic process that connects the learner, what the learner already knows, the environment in which knowing or learning occurs, and the activity through which the learner is participating when learning or knowing happens (Barab & Plucker, 2002). Learning is learner-centered, placing the student within a context and learning community where she actively participates in the learning process (Brown, Collins, & Duguid, 1989; Lave & Wenger, 1991; Vincini, 2003).

Knowledge that is "situated" can be useful outside of the original context. To enhance knowledge transfer from an academic setting, student classroom learning can be placed in a context that mimics the desired eventual environment as closely as possible. If learning can be placed in a context that has similar cues to the real-world application, then the learner has a greater chance of success outside of the classroom (Svinicki, 2008). Content is learned through activities and, as learners use the tools that practitioners use, they learn to think and act like "experts" in the field (Vincini, 2003).

Situated learning problems are often considered more motivating to students because they solidify the connections between real-world applications and what they are learning (Svinicki, 2008). These situated experiences are often collaborative and team-based, in which instructors model and coach learners during critical points in the activities (Vincini, 2003). Situated learning also allows for learners to observe the interchange between themselves and the culture in which they live and work (Garrison, Stevens, Sabin, & Jocuns, 2007). Lastly, situated learning is also closely related to the concept of "authentic assessment" in which real-world scenarios are used in evaluation of student performance. Authentic assessments are necessary to many popular instructional interventions, such as service-learning, since instructors are trying to gauge the real-world skills that they are hopefully nurturing in their students (Steinke & Fitch, 2007).

Engineering Education and an Inductive Model of Instruction

Traditional lecture teaching does not fit well within the constructivist model. The constructivist model aligns more with an inductive model of instruction. A definition of inductive learning offered by Prince and Felder (2006) is based on the constructivist model, suggesting that effective instruction must include the opportunity for students to construct knowledge for themselves, assimilating or rejecting their prior beliefs in light of the new experiences (Prince, 2006). In this context, students are presented with real-world problems to solve, are motivated to accommodate new facts and procedures when faced with gaps in their knowledge, and are presented with new information at that point by instructors or given instruction on how to find the knowledge themselves (Prince, 2006).

In engineering education, material is often presented deductively, in individual "silos" with little reliance on prior knowledge. Since cognitive research suggests that learning involves prior knowledge, it follows that engineering should be taught within the context of real-world, prior experience to facilitate student learning. Inductive instruction presents new information in the form of problems and context to which the students can relate, and so facilitates linking new information to existing mental structures (Prince, 2006). Traditional teaching also does little to contradict misconceptions previously held by students, and so inductive teaching also presents an option to discover misconceptions and structure real-world problems in a way that helps students readjust their thinking (Prince, 2006).

Research on knowledge acquisition also indicates that training students in problem-solving methods, in which they learn how to identify problems, assimilate new information, evaluate alternative solutions, and reflect on their own cognitive development, helps them transfer information from one setting to another (Prince, 2006). The likelihood that students are able to transfer the knowledge learned in the classrooms to other settings is more likely when the framework of the course mimics a real-world context, such as situated learning (Prince, 2006; Svinicki, 2008). This is parallel to gaining experience working in collaborative groups, which students encounter in the professional world. These practices are connected to cognitive research that is more constructivist in nature and provides a socio-cultural context, following the theories of Piaget, Vygotsky, and Kolb.

Instructional Techniques

Learning Cycles

While Piaget's research defined the stages of human intellect and how people transition to higher orders of thinking, he did not successfully discover a way to move people from one stage of intellect to the next. Several inductive instructional models involve learning cycles, in which students are engaged in a sequence of activities that lead them through complementary thinking and problem solving situations (Brophy, Klein, Portsmore, & Rogers, 2008; Prince, 2006; Schunn, 2009).One objective for a learning cycle approach is to engage students partly in styles in which they are comfortable and that facilitate learning for them, and partly in learning styles that are uncomfortable to them, but provide practice in ways of thinking that they might need in the professional world (Prince, 2006). The scientific learning cycle, developed by Renner and Lawson in 1973, draws on Piaget's theories to develop a method for enhancing students' intellectual development. In the scientific learning cycle, students are presented with a new experience to explore—or create a sense of disequilibrium—with minimal guidance (Lawson, Abraham, & Renner, 1989; Wankat & Oreovicz, 1993). Next, students are presented with the terms and material to help them assimilate new knowledge, assisting them in equilibrating the material. This might be in the form of lecture, readings, or guided discussion. Lastly, the students are engaged in further investigations or calculations to help them solidify the changed mental structure or apply it to new examples (Lawson et al., 1989; Wankat & Oreovicz, 1993). This process is slow, but shown effective in comparison with traditional lecture-based methods (Wankat & Oreovicz, 1993). Kolb's experiential learning model and the STAR Legacy model are two well-known examples of these types of learning cycles (Brophy et al., 2008; Prince, 2006). Learning cycles are clearly an inductive approach to teaching and several instructional methods follow this cycle, including inquiry-based, problem-based, and project-based instruction.

Inquiry-Based Instruction

For years, educators have touted the benefits of experiential, hands-on learning including laboratory investigations and interdisciplinary activities to enrich the curriculum (Markham, Larmer, & Ravitz, 2003). Inquiry-based instruction is often used in science classrooms and can be described as a teaching technique in which the students are engaged in "open-ended, student-centered, hands-on activities (Colburn, 2000)." Mimicking a constructivist environment, the teacher acts as a facilitator of student learning instead of provider of student knowledge. Inquiry-based learning begins when students are presented with a question or problem to be solved, then formulate questions, systematically analyze alternative solutions, and evaluate their conclusions based on the original context (Prince, 2006).

Inquiry learning is a fairly broad category of instruction that is sometimes considered to encompass several other teaching methods, such as problem-based and project-based instruction (Prince, 2006). Because of the breadth of inquiry-type instruction, it has often been differentiated into separate subcategories of instructional strategies. A few of the more common examples of constructivist teaching include: *structured inquiry*, in which students are given a problem and an outline for the method to solve it; *guided inquiry*, in which students are given a problem and then required to figure out how to solve it on their own; and *open inquiry*, in which students formulate the problem for themselves given a context or scenario (Colburn, 2000; Prince, 2006). Some instructors who are well-versed in inquiry instruction suggest starting students with structured inquiry and moving them slowly towards open-inquiry, while others recommend moving into open-inquiry right away (Prince, 2006).

Several published articles have analyzed inquiry-based instruction and conclude that it is more effective than traditional lecture-based instruction for academic achievement, critical thinking skills, reasoning ability and creativity (Prince, 2006). Other reviews recommend that good inquiry should focus on questions that students can answer through concrete investigation; emphasizing that problems and scenarios should be carefully structured to access students' prior knowledge but allow enough challenge to help them develop critical thinking skills (Colburn, 2000; Prince, 2006). Engineering design provides excellent opportunities to incorporate the characteristics of inquiry-based instruction when students are presented with or develop their own problems for which to design solutions.

Problem-Based Instruction

Problem-based instruction presents students with contextualized challenges for which they are required to work in groups to find meaningful solutions (Prince, 2006; Rhem, 1998). Research shows a higher quality of learning in students engaged in problem-based learning, however, not necessarily a greater amount of learning in the number of facts (Rhem, 1998). Problem-based learning has very little in the way of prescribed techniques, but the general idea remains rooted in constructivist theory that a teacher acts as facilitator instead of dispenser of knowledge (Prince, 2006). Student time in a problem-based classroom might be devoted to groups reporting on progress and identifying the next steps for their work, mini-lectures to clarify information common to all groups, and entire-class discussions (Prince, 2006). Instead of fact collecting, students work on creating meaning to integrate into their mental structure. Real-world problems give students the context and motivation for learning, and reflection allows for growth in higher-cognitive learning skills (Prince, 2006; Rhem, 1998). Because of the use of collaborative group work and personal responsibility for investigation involved with solving a contextualized problem, students often achieve higher levels of comprehension as well as developing solid knowledge-forming skills and social skills (Rhem, 1998). Students also receive immediate feedback while they are struggling with problems, and this keeps a constant flow of learning exchange between the teacher and student (Rhem, 1998).

Historically, problem-based instruction has been applied most often in the medical fields. Today, it has successfully been extended to other fields, including nursing, veterinary school, architecture, psychology, business and engineering. Traditionally, the medical school method of problem-based instruction includes groups of 7-10 students working on common problems under the supervision of an instructor or teaching assistant. In the medical school model, little formal class time is included (Prince, 2006).

Research on the effectiveness of problem-based learning that explores student gains in knowledge acquisition and skills development shows mixed results on students' knowledge acquisition. However, the gains are consistently positive when the assessment is conducted a length of time after the instruction. This suggests that students gain more knowledge in the short term using traditional methods, but retain knowledge for a longer period of time when problem-based instruction is used (Prince, 2006). For skills development, only positive results have been reported, indicating that problem-based instruction increases skills whether or not the assessment is conducted at the time of the instruction or afterwards (Prince, 2006).

Project-Based Instruction

Problem-based instruction is a forerunner and close relative to project-based instruction. Project-based instruction also has its roots in constructivist theory and experiential education. Again, students are an important partner in the learning process. Project-based learning has become popular as a result of the research in neuroscience and psychology on cognitive development. This research proposes two concepts: 1) learning is partly a social and cultural activity and 2) learners use their prior knowledge to explore, construct, and create new knowledge (Markham et al., 2003). Also, the refocus of some schools to adapt to a changing system in which students need both the knowledge and skills to navigate an increasingly global society has influenced the use of project-based instruction in the classroom (Markham et al., 2003). Basically, project-based instruction is the "attempt to create new instructional practices that reflect the environments in which children now live and learn (Markham et al., 2003)."

Project-based instruction also uses an inquiry process to engage students in learning through complex, real-world problems and carefully designed tasks (Markham et al., 2003). Distinctions are made between exclusively inquiry-based instruction, problem-based instruction, and project-based instruction. While students engaged in project-based learning are guided through the context of projects by a “driving question” or problems that creates motivation to learn the material, project-based learning specifies products to solve problems, often including multiple products to facilitate feedback and learning. This is accomplished through a final product, such as a design, model, device, or computer simulation, encouraging collaboration with other students, and using performance-based assessment to evaluate a range of skills and knowledge (Markham et al., 2003; Prince, 2006).The end product of “integrating and applying knowledge” is the primary focus of project-based learning, while the focus of problem-based learning is the acquisition of new knowledge to solve problems and the actual solutions may be less important (Prince, 2006).

Project-based learning is an evolving method of instruction. Currently, limited research exists on the effectiveness of this method in the classroom. However, what research does exist loosely follows the results from problem-based learning in that students demonstrate somewhat increased content knowledge with even deeper conceptual understanding and ability to extend the skills to other situations (Prince, 2006). In general, research around the effectiveness of PBL suggests that it creates a motivating environment for the teaching of basic skills, and increases students’ perceived connections between theory and practice, exhibition of professional skills at high levels, and encourages habits of mind that lead to lifelong learning and career success (Markham et al., 2003; Prince, 2006; Windschitl, 1999). Qualitative reports from teachers confirm that project-based instruction helps students practice self-management and encourages habits of mind that lead to lifelong learning and career success. Students engaged in project-based instruction have the perception of more support from their instructors, and see more connections between theory and practice (Prince, 2006). Instructors of project-based learning report seeing an increase in student competencies, improved quality of interaction with students, and improved contentment with teaching (Prince, 2006). Project-based instruction has been described as sensitive to the needs of diverse learners, creating opportunity for collaboration and communication, and motivational for bored or indifferent students (Markham et al., 2003). Drawbacks to PBL include the impacts of unbalanced team participation and the time and effort required to complete projects (Prince, 2006).

Project-based instruction is employed in engineering education most often at the senior capstone level and with increasing frequency in first-year engineering courses. However, many hybrid models of problem- and project- based instruction exist (Prince, 2006). For example, in some university courses, the goal of project design is the knowledge acquired during the process, rather than the actual product created (Prince, 2006).

Constructivist theory is based on the active participation of the learner. The teaching methods described above engage students in active learning, assisting them in forming new mental structures to assimilate into their existing cognition. Windschitl (1999) contends that problem-and project-based inquiry learning creates opportunity for “fluid intellectual transformations” that serve to facilitate learning (Windschitl, 1999).

Service-Learning

What is Service-Learning?

The idea of service-learning has been around since the 1860s, with the establishment of land-grant universities focused on agriculture and mechanics in the United States. As part of its mission, each land-grant university had a requirement of service to the community (Lima & Oakes, 2006). Service-Learning (SL) is an educational method through which students actively participate in community service as an integral component of their coursework, fostering both civic responsibility and scholastic abilities through the integration of academic instruction and community-based service. Research indicates that instruction in SL-centered experiences can improve academic learning of material and provide participants with a deeper understanding of the social context of their work, increasing technical, professional, and interpersonal skills (Astin, Vogelgesang, Ikeda, & Yee, 2000; Bielefeldt, Swan, & Paterson, 2009; Jacoby & Associates, 1996; S. R. Jones & Abes, 2004; Lemons, Carberry, Swan, & Jarvin, 2011; Lima & Oakes, 2006; Seider, Rabinowicz, & Gillmor, 2011; Zarske, Reamon, & Knight, 2011). Community needs define students' service tasks, providing them with the sense of responsibility for being members of a larger community and shifting their perceptions and commitment towards others and service-oriented careers (Jacoby & Associates, 1996; S. R. Jones & Abes, 2004). In properly designed and executed SL courses, both service and learning have "equal weight" (Lima & Oakes, 2006).

Distinct components of SL, once combined, make this instructional method attractive. These components include: service to an underserved area or people, diverse academic content, partnerships in and around the community, mutual learning by students and community participants, engaging and complex problems in complex settings that promote problem solving and critical thinking, and reflection (Lemons et al., 2011; Lima & Oakes, 2006). Of those, reflection is described as one of the most powerful tools for connecting service experiences to academic material and distinguishes service from traditional design (Astin et al., 2000; Tsang, 2000a).

Reflection becomes useful when it reinforces technical concepts of the course material for students, and helps them process the social and emotional experiences related to SL projects (Lima & Oakes, 2006). SL courses offer a platform for increasing the ability to self-reflect in engineering students. However, since emotive reflections might not be as accepted by the engineering community, which favors more logical and analytical methods of analysis, the goal for SL reflection in engineering is to gain an understanding about the social issues behind the services that students are providing (Tsang, 2000a). For example, Lemons (2011) noted that SL students were able to reflect on their process of learning while their peers (not engaged in SL) focused reflective pieces on the final product (Lemons et al., 2011). This important skill helps students internalize what they have learned and achieved, addressing the Accreditation Board of Engineering and Technology (ABET) criteria of providing "the broad education necessary to understand the impact of engineering solutions in a global, environmental, economic, and societal context" (ABET, 2011; Lemons et al., 2011).

Theories That Support Service-Learning and Project-Based Service-Learning

Within engineering, SL is frequently integrated into hands-on problem-based or project-based courses. More commonly referred to as project-based service-learning (PBSL), these courses are offered increasingly at universities who wish to engage students in learning design by solving real-world projects. The combination of service-learning and project-based learning provides an opportunity for individual growth in cognitive, social, and moral aspects, concurrently, leading to a greater maturation of the whole self (Bielefeldt, Paterson, & Swan, 2010). Individual development in these areas is based on the theories of Dewey, Piaget, Kohlberg, Vygotsky, and Kolb, discussed in greater depth previously in the Theories section of this document. More recently, other researchers, such as Lemons (2011), have chosen to describe

SL theory through the lens of metacognitive and self-regulated learning theories (Lemons et al., 2011). These theories find root in the dynamic processes of knowledge-building by the learner, or how students adapt their learning when they are aware of their own learning process (Lemons et al., 2011). In PBSL, this would happen most often during project reflection.

Another learning theory that supports PBSL in engineering courses is situated learning theory (SLT). Situated learning theory supports PBSL instruction on many levels. PBSL problems, similar to situated learning problems, are more motivating to students because they can see the connections between real-world applications and what they are learning (Bielefeldt et al., 2009; Svinicki, 2008). Situated learning and PBSL also both help in the formation of engineering identity for students (Bielefeldt et al., 2009; Stevens, O'Connor, Garrison, Jocuns, & Amos, 2008). Lastly, situated learning is closely related to the concept of "authentic assessment" in which real-world scenarios are used in evaluation of student performance. Authentic assessments are necessary to SL-related pedagogy as instructors try to measure the real-world skills that they are nurturing in their students (Steinke & Fitch, 2007).

Service-Learning Courses in Engineering

SL courses have been well-established in the social sciences, and are evolving in engineering colleges as a mechanism to elevate student communication skills and provide engineering students with meaningful, community-based learning experiences (Sullivan & Zarske, 2005; Tsang, 2000b). The potential impacts of SL relevant to these students can be grouped into five main categories: student knowledge, student skills, student attitudes, recruitment/retention/diversity, and post-educational professional performance (Bielefeldt et al., 2009). However, service-learning is still not generally (or universally) integrated throughout engineering education curricula, and a majority of SL in engineering coursework is found in senior capstone design (Bielefeldt et al., 2010; Freeman, 2011; Moskal, Skokan, & Mun, 2008; Tsang, 2000a). More recently, attention has been given to the educational and psychological outcomes associated with SL, driving current programs to include engineering skills and attitudes considerations in their program assessment (Harding, Slivovsky, & Truch, 2010). In a few first-year programs, PBSL has specifically been reported to positively impact students' perceptions of their roles as engineers, awareness of socially responsible opportunities, and satisfaction with their first-year-experiences (Coyle, Jamieson, & Oakes, 2003; Freeman, 2011; Harding et al., 2010).

Increasingly, assessment of programs engaged in SL efforts report multiple benefits and challenges for implementation. These serve as road maps for others to follow as they consider including SL components into their engineering curricula. For example, at the University of California, Los Angeles's Higher Education Research Institute longitudinal study of more than 22,000 college undergraduates concluded that the use of SL pedagogy has significant positive effects on students' academic performance (grade point average, writing skills, and critical thinking skills), leadership skills, and increased commitment to continued civic participation (Astin et al., 2000). This study suggests that SL be tied to a student's major area of study and adequate training in SL be provided (Astin et al., 2000). In another study, 68% of students engaged in the National Engineering Projects in Community Service (EPICS) program reported that participation in SL positively impacted their determination to continue in engineering (Coyle et al., 2003). The remaining 32% of students who did not respond positively were already firmly committed to engineering before their EPICS SL experience and continued to be afterwards (Coyle et al., 2003). Other studies have found similar positive benefits of SL in the classrooms on learning subject matter, personal and interpersonal development, civic responsibility, and self-efficacy (Duffy, Barrington, & Heredia, 2009; Freeman, 2011; Harding et al., 2010). Fisher et al. (2005) suggest that the SL context is more important than pedagogy; students in SL sections rated the course higher than their peers in non-SL sections on instruction and climate, irrespective of the faculty member teaching the course (Fisher, Zeligman, & Fairweather, 2005).

Among reported concerns in the use of SL in engineering undergraduate courses is the idea of students providing professional services. However, Tsang (2000) provides the view that, although student service cannot replace professional engineering, it can provide a blueprint for community organizations and local/state agencies to determine whether further professional engineering is needed (Tsang, 2000a). When funding is scarce, these agencies can use student work as a springboard to leverage additional outside sponsorship (Tsang, 2000a). Liability—the condition of being subject to legal obligation—is another concern often raised by faculty due to the abundance of engineering designs that involve products used by people. Tsang suggests that most colleges have liability guidelines for senior capstone projects that are suitable (Tsang, 2000a). Lima and Oakes (2006) also outline several steps for addressing liability issues in their SL textbook and advise students to partner with their professor or community member in a risk management plan (Lima & Oakes, 2006). Another option is to replace actual clients with theoretical clients. Recent research indicates that in first-year engineering undergraduate classes, a theoretical SL context based on actual scenarios is often just as effective as experiential SL projects (Freeman, 2011).

Many of the positive student outcomes reported in the literature on SL experiences in undergraduate engineering programs fall into similar categories, such as: critical thinking skills, professional and technical skills, identity and self-efficacy, interpersonal skills/awareness, attitudes towards community service, and recruitment/retention/diversity. Bielefeldt (2010) also offers a list of enhanced skills achieved by the addition of SL to project-based courses, including greater complexity, confidence, critical thinking, leadership, and creativity (Bielefeldt et al., 2010). Nine of these programs and positive student outcomes are reported in Table 2.1.

Table 2.1. Examples of university service-learning activities and positive outcomes described in the literature

University (alphabetical listing)	**Service-Learning (SL) Activity** and **Number of Participants in Reported Study**	Critical Thinking Skills	Professional and Technical Skills	Identity and Self-Efficacy	Interpersonal Skills / Awareness	Attitudes towards Community Service	Recruitment / Retention / Diversity
California Polytechnic State University (Harding et al., 2010)	Introduction to Materials Engineering design sequence (n=36)			X			X
Colorado School of Mines (Moskal et al., 2008)	Humanitarian Program (n=~2,500)					X	X
Michigan State University (Fisher et al., 2005)	Electronic Instrumentation and Systems (n=1,236)	X	X				X
Michigan Technological University (Hokanson, Phillips, & Mihelcic, 2007)	Undergraduate International Senior Design, minor in International Sustainable Development Engineering, and master's International Engineering Program						X
Tufts University (Lemons et al., 2011)	A sample of engineering undergraduate students across diverse disciplines (n=10)	X			X		
University of Colorado Boulder (Bielefeldt, Amadei, & Sandekian, 2008)	Introductory Environmental Engineering course, EVEN 1000 (n=28)					X	
University of Colorado Boulder (Zarske et al., 2011)	First-Year Engineering Projects course (n=66)		X				X
University of Massachusetts Lowell (Duffy, Barry, & Clark, 2007)	SLICE Program, incorporates PBSL projects into existing courses throughout the curriculum (N=740)					X	X
Virginia Tech (Williams, Goff, Terpenny, Knott, & Gilbert, 2009)	ROXIE Program, Exploration of Engineering Design first-year course (n=185)		X				

Service as a Motivator to Learn Engineering

Learning Through Service (LTS) is a term that encompasses both curricular-based SL and extracurricular service opportunities, such as Engineers Without Borders (Canney & Bielefeldt, 2012). It seems as if LTS appeals to a wide audience because of its roots in helping the greater community, or social good. When asking students what drives them to study engineering, social good consistently appears ranked among top motivational factors by both males and females (Atman et al., 2010; Duffy et al., 2009; Pierrakos, Beam, Constantz, Johri, & Anderson, 2009; Sheppard et al., 2010). Participating in LTS engineering projects for social good (such as humanitarian projects, Engineers Without Borders) or other non-engineering service work, has a positive impact on competence, aiding students in becoming potentially more responsible engineers, socially responsible citizens, and benefiting the community at the same time (Duffy et al., 2009; Freeman, 2011; Palmer, McKenna, Harper, Terenzini, & Merson, 2011). Motivation does not seem to alter much over the course of an undergraduate degree program, suggesting that some of these factors may occur significantly pre-college or during the first years of undergraduate degree studies (Sheppard et al., 2010). For students who participate in LTS opportunities more often, more positive attitudes toward service and social good may result (Bielefeldt et al., 2008). However, the often- referenced APPLES study suggests only a modest correlation between social good motivation and frequency of engineering students' extracurricular participation (Sheppard et al., 2010). In comparison with other majors, Ohland (2008) found that engineering students were average in terms of their involvement in community and volunteer service (59%) (Ohland et al., 2008). It is worth mentioning that another success of LTS projects is the positive impact on the community, with community partners' understanding of engineering increasing through real-world interactions with the engineering students.

Impacts on Retention from Service-Learning

First-year students' belief in the usefulness of engineering has been positively correlated to their plans on choosing engineering careers (B. D. Jones, Paretti, Hein, & Knott, 2010). Several programs report that participation in SL positively impacts students' determination to continue in engineering (retention) or was a factor in selecting the program (recruitment) (Coyle et al., 2003; Duffy et al., 2009; Fisher et al., 2005; West, Duffy, Heredia, & Barrington, 2010). Research conducted at the University of Massachusetts Lowell found that consistently more than 60% of students surveyed from year to year indicated that engagement in service-learning caused them to stay in engineering (Duffy et al., 2009). Research around similar SL engineering design activities that include the pre-college (grades K-12) setting also benefitted the students' knowledge and interest in engineering (Moskal et al., 2008).

Impacts on Women and Minorities from Service-Learning

Retaining the interest of women and students of color in engineering is also reported to improve at the K-12 and undergraduate levels when subject matter is placed in a social context and cooperative, interdisciplinary approaches to problems focus on holistic and global impacts (Matyas & Malcolm, 1991; Mihelcic et al., 2008; Noddings, 1992; J. Oakes, Gamoran, & Page, 1992; Seider et al., 2011; Zimmerman & Vanegas, 2007). SL research at the K-12 level also indicates that a service-learning context may be a key factor in the recruitment of minority and female students into engineering offerings (Thompson, Turner, & Oakes, 2008). This positive impact is echoed in undergraduate research on retention of female engineering students (Duffy et al., 2009).

The belief that engineers contribute to improving society, or engineering for a social good, seems to resonate with a diverse group of students throughout the literature. Anecdotally, showing students the broader impacts of engineering on society and allowing them to make immediate positive contributions using their new engineering skills has already been confirmed as more attractive to underrepresented students, especially women (Hokanson et al., 2007; Moskal et al., 2008). Overall, an overrepresentation of women may exist in SL-based courses and programs as females are generally more inclined towards SL and even volunteer to participate in SL at higher rates than their male counterparts (Bielefeldt et al., 2008; Coyle et al., 2003; Duffy et al., 2009; Freeman, 2011; Matusovich, Follman, & Oakes, 2006; Mihelcic et al., 2008; Seider et al., 2011).

For example, an overrepresentation of women is present in leadership roles within student chapters of Engineering without Borders (EWB). In 2007, EWB—whose mission is to partner with disadvantaged communities to improve quality of life factors while developing internationally responsible engineering graduates—had equal or higher representation of women in leadership positions in 23 of 24 established chapters (Zimmerman & Vanegas, 2007). This report and others suggest that education in sustainability in academic environments through global SL paths can also be useful for the recruitment and retention of women in engineering (Mihelcic et al., 2008; Zimmerman & Vanegas, 2007). Also, Seider (2011) offers that female students were more likely to participate in SL opportunities and were more influenced by the service experiences in which they participated at a competitive Catholic university in a large American city (Seider et al., 2011). Even though Bielefeldt (2008) discovered few significant differences in the self-reported attitudes of the SL students based on gender (e.g., connectedness to the community and career benefits of helping), it also appears that females are more likely to agree that SL helped keep them in engineering (Bielefeldt et al., 2008; Duffy et al., 2009).

Combining project-based learning and service-learning (PBSL) has the potential to foster greater cultural awareness, community-mindedness, and greater flexibility in defining and solving engineering problems. PBSL instructional methods actively engage learners in complex, carefully designed problems that benefit real communities or clients. Using a method of practicing engineering in a community context, partnered with a strong emphasis on teamwork and reflection, PBSL programs may be effective approaches to recruit and retain more students, including women and students of color, into the pipeline of engineering education and the engineering workforce (Bielefeldt et al., 2009; Sullivan & Zarske, 2005).

Identity

What is Identity?

Many researchers explain the idea of personal "identity," discussing the importance of student identity in both the process of learning and whether a person considers the learning to be a success or failure. Generally thought of as internal, identity is frequently associated with intrinsic motivation and the type of person that one is currently or desires to be (Matusovich, Streveler, Miller, & Olds, 2009). Both intrinsic motivation and desired future identity can greatly influence current behaviors inside and outside of the learning environment.

The decades of research surrounding identity allow for a comprehensive description of the complexities in identity formation. Several prominent theories assert that an individual has multiple identities that work together to form his/her prevailing identity. For example, Jackson (1981) describes seven identities of an individual, including associational, kinship, occupational, peer, recreational, religious, and romantic. According to Jackson, a person's main identity is essentially an intertwined system of these seven identities, and the one that a person is most committed to takes a higher rank than the other identities (Jackson, 1981). Also widely referenced is James Paul Gee, who put forth that people have multiple identities that are "connected to their performance in society" (Gee, 2001). Gee describes multiple identities that fit into four discrete categories; nature-identity (a state), institution-identity (a position in society), discourse-identity (an individual trait that is recognized by others) and affinity-identity (experiences in groups). These four categories interact in tandem to form a person's individual identity (Farnsworth, 2010; Gee, 2001; Matusovich, Barry, Meyers, & Louis, 2011).

Lave and Wenger's situated learning theory is another central theory that influences discourse on identity, describing how budding learners relate themselves to what they are learning and how this changes over time (Lave & Wenger, 1991). The literature abounds with examples of identity-related situated learning and communities of practice. Simply put, identity evolves as an individual relates to a discipline, encompassing a multi-sided process of how an individual identifies herself as well as how she is perceived by others in the learning community (Harre & Moghaddam, 2003; Stevens et al., 2008). In other words, identity is made up of two aspects, the self (personal) and perceptions by others (social) (Beam, Pierrakos, Constantz, Johri, & Anderson, 2009; Gee, 2001; Jocuns, Stevens, Garrison, & Amos, 2008; Stevens et al., 2008). It is something personally experienced (as in "I am an engineer"), as well as something ascribed and maintained by others (as in "you are an engineer").

Sfard and Prusak (2005) define identity as a "collection of stories" about an individual that are considered significant (Sfard & Prusak, 2005). They describe actual and designated identities or the narration of actual happenings and expected happenings in the future. Designated identities are "products of collective storytelling," in which the storyteller's and listeners' perceptions interact to influence identity (Sfard & Prusak, 2005). Complementing other theories, "identity as stories" offers an explanation as to how people might integrate new experiences internally, assimilating both their self-perceptions (personal) and the possibly differing perceptions of observers (social).

The concept of an identity that is "socially produced" is central to understanding how aspects of identity are adopted or prioritized (O'Connor, Perhamus, Seward, & Stevens, 2006). That identity is influenced by the perceptions of others—fitting within the group—can have a meaningful influence on a person's behaviors and choices, including motivation and professional persistence (Beam et al., 2009; Matusovich et al., 2011; Pierrakos et al., 2009; Plett et al., 2011). In other words, how much the perception of others influences a person's own identity depends on how strongly the person considers himself part of that group (Pierrakos et al., 2009). As students interact with a discipline-specific learning community, such as engineering students, they begin to form discipline-based identities that result in a cycle of individual identity and communities reinforcing each other (Pierrakos et al., 2009; Plett et al., 2011).

It makes sense that identity is not static but evolves over time. As students develop and mature, they alter their identities throughout their educational experiences. Wenger discusses an identity paradox in which a person needs an identity of participation to learn but needs to engage in the learning process to acquire identity of participation (Wenger, 1998). Over time, both a student's connection to her academic environment (classroom and major) as well as perception of herself, are strongly related to her decision-making process and sense of career identity (Matusovich et al., 2009; Plett et al., 2011). Pierrakos refers to this change as identity transformation (Pierrakos et al., 2009).

Identity with the Engineering Profession

Professional identity is a form of social identity that that differentiates how people relate within professional groups—in this context, engineering. It also develops over time, and includes shared attitudes, knowledge, and skills characteristic to members of that profession (K. Adams, Hean, Sturgis, & Clark, 2006; Beam et al., 2009). A student's perception of being part of an engineering discipline and how much of his self is intertwined with the engineering discipline can influence post-graduation career choice (Matusovich et al., 2011; Plett et al., 2011). Several researchers have developed studies to determine the factors that shape students' engineering identities and how much their identities affect their decisions to stay in engineering (Atman et al., 2010; Chachra, Kilgore, Loshbaugh, McCain, & Chen, 2008; Jocuns et al., 2008; O'Connor, Garrison, Jocuns, & Stevens, 2009; Pierrakos et al., 2009). Self-reported knowledge plays a large role in professional identity, suggesting that students who know more about the profession are more likely to relate themselves to the profession (K. Adams et al., 2006). Other factors that reportedly contribute to professional identity include understanding of team dynamics, cognitive flexibility, work experience, and students' self-perceptions of their problem solving, technical, and theoretical knowledge (K. Adams et al., 2006; Matusovich et al., 2009; Milano, Parker, & Pincus, 1996). However, the many obvious confounding factors in the study of identity make it difficult to quantify (Matusovich et al., 2009). For example, students who do not see themselves in common engineering images may need to work more to augment their identities to fit in engineering careers (Jocuns et al., 2008).

Stevens asserts that engineering identity, accountable disciplinary knowledge, and navigation through an institution of engineering education (such as a college) are all interrelated in the process of becoming an engineer (Stevens et al., 2008). Furthermore, this qualitative ethnographic research describes how different student identities can be a function of how their home institution labels them as "engineering students" or not (Stevens et al., 2008). Jocuns adds that students' identities (sometimes changing from hopeful to mundane) can also be impacted by their perception of engineers due to a lack of real engineering experiences in undergraduate careers (Jocuns et al., 2008). Some of this has been described as the impact of "sponsorship" by the engineering discipline on an individual student's identity (Atman et al., 2010; O'Connor et al., 2006).

It is agreed that individual students develop a composite engineering identity through a variety of sources and pathways. However, with all of the research on what impacts engineering identity, the current literature does not offer much insight or guidance on a path for students to develop their professional identities; nor does it suggest what universities might consider doing to improve students' identification with engineering (Matusovich et al., 2011). The need exists for further research on student identification with engineering, how identity and social identity motivate students to pursue engineering degrees and how different views of the nature of engineering manifest in developing engineering identity (Atman et al., 2010; Matusovich et al., 2011; O'Connor et al., 2006).

Gender and Identity

In describing any differential effects of identity development by gender, the results are mixed. While the Academic Pathways Study (APS) suggests that pathways to engineering identity do not vary considerably by gender or ethnicity, other research suggests that engineering identity does vary over time with gender (Atman et al., 2010; Beam et al., 2009; Chachra et al., 2008; Pierrakos et al., 2009). Gender is a significant predictor of professional identity in other disciplines, and the study of more than 1,000 first-year health and social care students by Adams et al. (2006) suggests that males and females not only have differing levels of professional identity but may experience it differently (K. Adams et al., 2006). This is supported by a Pierrakos study (2010) of first-year engineering students' identity with the discipline that suggested female students conceptualize engineering in a more abstract manner than males (Pierrakos, Beam, Watson, Thompson, & Anderson, 2010). Despite the varying results presented in the literature on how gender plays a role in developing identity, it is agreed that the perception of engineers or the engineering profession has the potential to vary across gender, ethnicity, and year of study.

One examination of the APS data by Chachra et al. (2008) indicated no significant differences in the self-reported identity scores of males and females during the first year of engineering undergraduate courses. However, during the second year, they found that female students had a greater degree of personal identification with engineers and male students had a higher perception of public regard for engineers (Chachra et al., 2008). Chachra's group then looked for any differences between engineering identity as a student and identification with the profession of engineering. This study posited that identification with engineering between male and female students differs since the genders have different initial perceptions of engineering. They based their analysis on several hundred students' responses when asked to select the six most important skills for engineering design. The student choices, analyzed by gender, differed by year and also over time, suggesting that male and female students have different perceptions of engineering and that these perceptions evolve over time. They found little difference in the overall amount of identification with engineering between males and females in the first and second year of engineering undergraduate studies; however, it was apparent that towards the end of their sophomore year male and female students are actually identifying with different definitions or activities within the engineering discipline (Chachra et al., 2008).

One possible confounding factor in accurately describing the evolution of engineering identity in genders is student confidence and efficacy. Research indicates that most students feel confident about succeeding in engineering based on their previous academic abilities and performance (Hutchison-Green, Follman, & Bodner, 2008; Sheppard et al., 2010). Work by Hutchinson-Green (2008) in engineering confidence showed that performance comparisons (including speed, mastery, and team contribution), i.e., how they were doing compared to their peers, had a great influence on students' evolving engineering efficacy beliefs (Hutchison-Green et al., 2008). In this and other reports, males consistently rank their skills and abilities higher than their female counterparts (Atman et al., 2010; Besterfield-Sacre, Moreno, Shuman, & Atman, 2001; Hutchison-Green et al., 2008).

Another related line of research that demonstrates an impact on engineering identity by gender is the presence of more female faculty members as role models for women students. It is important to have women students and faculty for men and women, especially those who demonstrate a work and family balance (Amelink & Creamer, 2010). While the development of engineering identity is a major focus of most engineering degree granting institutions, Chachra suggests that the development of engineering identity by gender is more complex and multilayered (Chachra et al., 2008). Future research could look at how both genders develop their identities with the engineering profession and what particular activities or practices facilitate this process.

Service-Learning and Identity

The slowly growing body of research on identity and service-learning indicates that participation in SL courses leads to significant and enduring increases in identity (Batchelder & Root, 1994; S. R. Jones & Abes, 2004). Batchelder and Root (1994) report on a study of 96 students from a small, Midwestern, liberal arts college (Batchelder & Root, 1994); 48 of these students participated in an SL course and 48 did not, and all students were taught by the same instructors. An analysis of quantitative survey scores indicated that SL did not significantly predict individual identity processing; however, the students in the SL course did increase in identity development during later qualitative journal entries. The researchers surmised that the survey items related to SL in their study were not the same indicators as would predict identity (Batchelder & Root, 1994).

More qualitative research studies conclude that the long-term effects of SL lead to a more integrated identity with regard to in citizenship and social responsibility (S. R. Jones & Abes, 2004). Repeatedly reported, previously held notions of students' self that are challenged within the unfamiliar domains of a community-based context, along with the support to successfully engage in these contexts, allow for more complex reconstruction of students' identity towards socially responsible work and open-mindedness towards diverse cultures (S. Chang, Anagnostopoulos, & Omae, 2011; Farnsworth, 2010; S. R. Jones & Abes, 2004). Unfortunately, these studies were conducted with undergraduate liberal arts and education majors; no reported research exists on whether the opportunity to engage in engineering for "social good" specifically increases engineering identity and actual persistence into engineering related careers.

First-Year Engineering Programs

In a recent literature review on first-year engineering programs during the last five years, Paretti and Cross (2011) conducted an extensive literature review of first-year programs and found that experiences were varied from small-scale to large-scale projects, spanning one semester to a full year. They summarized 50 programs reported in the literature in the last five years and—not surprisingly—found that assessment generally fell into two categories: retention (including attitudes, motivation) and design skills (Paretti & Cross, 2011). Most measures were 5-point Likert-scale surveys that queried student satisfaction, attitudes towards engineering, and self-reported learning gains, but some programs included GPA and self-reports on majors and career goals (Paretti & Cross, 2011). The researchers noticed that, unfortunately, few measureable outcomes to describe success were similar across programs. They conclude that the large number of papers written about first-year programs is testament to the importance and passion of engineering educators for improving student experiences, but a strong community of sharing is missing. (Paretti & Cross, 2011)

PBL and PBSL in First-Year Engineering Programs

Often team-based in nature, first-year engineering PBL courses have resulted in increased gains in knowledge across genders and can be effective in increasing students' self efficacy and confidence in using the engineering design process (Constans & Kadlowec, 2011; Harding et al., 2010; Olsen & Washabaugh, 2011; Sheppard et al., 2010). This is impactful, especially in light of the results from the prominent APPLES study that concluded that first-year students tend to enter their engineering courses already highly confident in their abilities to solve open-ended problems, their math and science knowledge, and professional/interpersonal skills (Sheppard et al., 2010). For women who may have rated their knowledge and design skills lower at the beginning of their first-year PBL experience, Knight et al. (2003) reported a closing of the gender gap on those skills by course end (Knight, Carlson, & Sullivan, 2003).

APPLES reports further on the first-year program model. As with seniors, participation in non-engineering extracurricular activities is a positive and strong predictor of confidence in professional and interpersonal skills. It is possible that students with strong leadership and interpersonal self-concepts seek out these non-engineering experiences even in the first college year, looking for a broader range of activities and exposure to different types of people than those they might find in their engineering programs. It is also possible that these non-engineering extracurricular activities serve to build students' confidence in their abilities to work and communicate with others (Sheppard et al., 2010).

Can this be explained by first-year students being very idealistic following successful high school careers? Several programs echo that first-year students expect to do well in their PBL courses. Jones (2010) found that first-year students came into the program valuing engineering as useful, confident in their self-efficacy to succeed, and intending to pursue engineering careers. All of these self-reported values decreased but remained relatively high (in the top third of the rating scale) with no difference by gender (B. D. Jones et al., 2010). Even though their self-reported attitudes show an overall decline, most programs still report that PBL students out-perform their first-year peers in similar courses and demonstrate the ability to do just as well as their third-year peers on exams and homework (Constans & Kadlowec, 2011; Olsen & Washabaugh, 2011). When combined with a service-context, PBSL in first-year programs has specifically been reported to positively impact students' perceptions of their roles as engineers, awareness of socially responsible opportunities, and satisfaction with their first-year-experiences (Coyle et al., 2003; Freeman, 2011; Harding et al., 2010).

Among mixed results from studies that looked at differences in confidence and competence between first-year students of different genders and ethnicities, the majority of studies report lower confidence and beliefs of competence for female students (Besterfield-Sacre et al., 2001; B. D. Jones et al., 2010; Sheppard et al., 2010). Several studies look at the influence of mentoring on first-year students, concluding that it is important to engage women students and faculty mentors for both young men and women students to increase the retention of capable and interested students (Amelink & Creamer, 2010; Meyers, Silliman, Gedde, & Ohland, 2010).

Retention and First-Year Engineering Programs

With the U.S. facing a shortage of trained engineers (Moskal et al., 2008), the resulting push to improve methods of undergraduate engineering instruction has led to more attention on first-year engineering experiences. Further, it is suggested that mastery project-based design experiences should come early in academic pursuits, allowing freshmen to become engineers "right away" (Carlson & Sullivan, 2004; Hutchison-Green et al., 2008; Milano et al., 1996; Olsen & Washabaugh, 2011; Watson, Pierrakos, & Newbold, 2010). Retention is obviously a desired outcome, and Paretti (2011) noticed in an extensive literature review that across majors and institutions a gap exists in defining expected levels of success between the well-vetted capstone courses and low expectations for first-year programs (Paretti & Cross, 2011).

Research suggests that open-ended, hands-on PBL engineering design courses are key to recruitment and retention of undergraduate engineering students. Utility of and identification with engineering are highly related to students' career goals, with first-year students' beliefs in the usefulness of engineering positively correlating to their plans for choosing engineering careers (B. D. Jones et al., 2010). Research at the University of Colorado Boulder (CU) examined the retention of their undergraduate engineering students (n=5,070) over eight semesters by comparing 2,128 students who completed a First-Year Engineering Projects course with 2,942 students who did not take the course. Results showed that students who experienced hands-on design in their first year were retained to graduation at 64% compared to the national engineering retention rate of 56% (Fortenberry et al., 2007; Knight, Carlson, & Sullivan, 2007). From the reports on PBSL programs, it is conceivable that first-year project-based courses that offer opportunities to immerse students in hands-on engineering design for specific or theoretical clients demonstrate the social value and relevance of the trade in a concrete way. Incorporating real-world problems may increase first-year students' beliefs about the usefulness of engineering, further increasing their identification with engineering and retention (B. D. Jones et al., 2010). Overall, the existing literature on project-based engineering design experiences indicates that this method is one of the more effective available in training future engineers.

Persistence in Engineering Education

A translation problem is associated with identity between undergraduate engineering education and integration into the real-world profession. Matusovich et al. (2009) noticed that students generally have little idea of what the profession of engineering means in terms of work challenges, daily tasks, relationships and/or responsibilities after four years of engineering education (Matusovich et al., 2009). Research strongly suggests that a difference exists between the idealized version of the profession and the actual work of the profession. Other studies conclude that it is likely that individuals share the same group identity, but translate this to mean different things in practice (K. Adams et al., 2006). There is a subtle difference between retention of a student population and persistence of an individual student in a desired discipline. This section will discuss impacts on individual persistence, as found in the literature.

What Impacts Persistence?

It is well known that engineering has a persistence problem that is not strictly connected to academics. Research concludes that students who persist in engineering and students who do not are equally academically prepared to succeed in engineering (Pierrakos et al., 2009; Seymour & Hewitt, 1997). The Seymour and Hewitt study (1997) found that students who switched out of STEM majors most often cited factors that were "structural or cultural," including a lack of identification with STEM-major careers (Ohland et al., 2008; Seymour & Hewitt, 1997). Pierrakos noticed that, while uniform low identity exists at the first-year level, "persisters" (students who remained in engineering) had at least some identification with engineering while "non-persisters" (students who switched out of engineering) had none (Pierrakos et al., 2009).

Student identity with engineering plays a part in the decisions to persist in engineering. Interactions with other engineering students and the activities that engineers engage in is positively associated with an intent to major in engineering (and eventually persistence) (Atman et al., 2010; Beam et al., 2009; Loshbaugh & Claar, 2007; Stevens et al., 2008). Early non-persisters, (students who decide to leave engineering sooner than other non-persisters) are less firm in their intentions during their first year of college, and this difference increases over time with non-persisters who leave during later years (Eris et al., 2010).

Actual engagement in engineering is one issue that is repeatedly mentioned as a concern for engineering students (Fortenberry et al., 2007; Ohland et al., 2008). For example, Ohland's group hypothesized that persistence in engineering undergraduate degree programs is related to a student's disengagement in engineering courses and engagement in non-related courses (Ohland et al., 2008). Yet, they found that engineering students were just as engaged as other majors. In fact, the Persistence in Engineering (PIE) data suggests that student disengagement with engineering increases over time for both persisters and non-persisters (Ohland et al., 2008). Noting that some students leave engineering because of the high number of engineering course requirements that have the consequence of limiting the opportunities for enrollment in other courses and not having time to nurture other parts of their identities, Loshbaugh suggests that allowing students to explore studies outside the engineering curricula might improve overall student retention (Loshbaugh & Claar, 2007). This is echoed by Lichtenstein who defends allowing each student time for general education and educationally enriching experiences to increase engagement and persistence (Lichtenstein, McCormick, Sheppard, & Puma, 2010).

While retention in engineering is comparable and in some cases higher than other majors (such as arts & humanities, business, and social sciences), student interactions with other engineering students seems to be significantly related to whether students see themselves finishing engineering degrees and whether they see themselves in engineering in 10 years' time (Amelink & Creamer, 2010; Ohland et al., 2008).

Motivation is another issue often correlated with persistence, indicating that personal motivation and enjoyment in engineering leads to a stronger commitment to persist (Atman et al., 2010; Sheppard et al., 2010). When asked what appealed to them about engineering, male students more likely responded monetary incentives, while female students more often mentioned helping people and society (Pierrakos et al., 2009). These engineering for social good factors are often cited as one of the top self-reported motivational factors for students to study engineering for both males and females, indicting the importance that engineers contribute to improving society (Atman et al., 2010; Duffy et al., 2009; Pierrakos et al., 2009; Sheppard et al., 2010). Engineering for social good as a motivation for persistence is further supported through a study by Stevens and colleagues on the importance of engineering identity in student persistence that led to the recommendation of increasing the opportunities for strengthening identity in the early years of an engineering education by helping students identify engineering as a profession that has benefits beyond material existence (Stevens et al., 2008).

A study by Beam (2009) found exposure to engineering and knowledge of engineering disciplines were the two factors most impacting persistence, and that increased exposure—such as simply knowing a family member or someone who was an engineer—led to greater professional identity and, by extension, persistence in engineering (Beam et al., 2009). In general, engineering persisters have more knowledge of and overall exposure to engineering than non-persisters (Pierrakos et al., 2009). The Center for the Advancement of Engineering Education (CAEE) reports that as few as 20% of first-year engineering students had any significant exposure to engineering before coming to an engineering college (Atman et al., 2010). These students had little knowledge of what engineers “do”—an aspect that is essential to forming an identity as an engineer. The case may be worse for females, who are more likely to mention not having any exposure to engineering prior to college (Pierrakos et al., 2010). Several researchers have also concluded that, compared to other STEM fields, an overall lack of engineering-related curricula in K-12 essentially leads to students’ lack of understanding of the engineering field (Beam et al., 2009; Stevens et al., 2008).

Overall, recommendations for increasing student persistence have included the exposure of more pre-college students to engineering, offering more first-year college engineering students exposure to experiences within a greater representation of the breadth of engineering, and encouraging increased student engagement in extracurricular engineering-related groups and activities (Beam et al., 2009; Hutchison-Green et al., 2008; Pierrakos et al., 2009; Watson et al., 2010).

K-12 Engineering

Impacts of K-12 Engineering

Research suggests that retention in undergraduate engineering studies may be related to early exposure to engineering and knowledge of engineering disciplines, leading to greater professional identity, learning of higher level technical and professional skills, and persistence in engineering (Beam et al., 2009; Fantz, Siller, & DeMiranda, 2011; Pierrakos et al., 2009; Schunn, 2009). Even something as simple as personally knowing a family member or another person who is an engineer makes a difference; those people often provide ongoing support, connections to opportunities in the field, and an overall familiarity with the discipline (Beam et al., 2009). Fantz (2011) compared first-year engineering undergraduate students at Colorado State University who had pre-collegiate experiences to those who did not in order to gain insight into possible sources of self-efficacy (Fantz et al., 2011). Overall, a higher exposure to engineering content during K-12 led to higher self-efficacy in undergraduate first-year engineering, especially semester-long classes at the high school or middle school levels (which has also been suggested to lead to increased individual performance and persistence) (Fantz et al., 2011). It is also relevant to mention that even though just a small number of grade K-12 students may go on to engineering careers, the exposure to engineering at the K-12 level can also result in more technologically literate citizens and possibly increased diversity of engineers (Schunn, 2009; Sullivan & Zarske, 2005).

Engineering design at the pre-college level has exploded through the introduction of nationwide competitions, such as FIRST (For Inspiration and Recognition of Science and Technology) robotics, and partnerships with local engineering colleges. In 2006, the National Academy of Engineering (NAE) and the National Research Council (NRC) responded to the increase in K-12 engineering initiatives by forming the Committee on K-12 Engineering Education. This group investigated what defines engineering in K-12 settings and sought to identify any best practices that might exist for K-12 engineering instruction and learning (Katehi, Pearson, & Feder, 2009). The Committee spent many months engaged in rigorous research and discussion on these topics and the resulting 2009 publication, *Engineering in K-12 Education: Understanding the Status and Improving the Prospects,* offered an in-depth analysis of existing K-12 engineering curricula, the science of learning engineering in the K-12 setting, and evidence supporting the effectiveness of teaching engineering in the K-12 arena. The investigation found evidence of improved learning and achievement in science and mathematics, as well as an increased awareness of engineering as a career, as a result of pre-college engineering experiences (Katehi et al., 2009). They also expressed the need for more research around potential impact on students from engaging in engineering at the K-12 level.

Informed by research at the undergraduate level, recommendations for K-12 engineering programs include the incorporation of hands-on, real-life applicable, and project-based experiences coupled with academic rigor (Fantz et al., 2011). Thus, K-12 engineering work is often grounded in the existing research on inquiry-based and project-based learning—using an inquiry process to engage students in learning through exposure to complex, real-world problems, reflecting the environment in which they live and learn (Brophy et al., 2008; Markham et al., 2003). Evidence at the K-12 level shows that a project-based instructional method provides a motivating environment for the teaching of basic skills and increases student understanding of more complex problems, as well as student exhibition of higher professional skills and creativity, than students that are taught traditionally (Brophy et al., 2008; Markham et al., 2003). Analysis of hands-on engineering design activities in the K-12 setting also demonstrates an increase in students' STEM content knowledge and interest in engineering (Zarske, Yowell, Sullivan, Knight, & Wiant, 2007).

The NAE Committee on K-12 Engineering Education noted that the real-world problem solving nature of engineering led to an improved learning of the fundamental science and math principles that students explore early in their educations and to an increased interest in these topics at the K-12 level (Katehi et al., 2009). The Committee recommended that design could be enhanced for K-12 students by placement in a more personal or local-community/real-world context. This recommendation provides support for the use of PBSL as a mechanism for teaching core engineering concepts such as optimization and systems thinking in the K-12 classroom. Such client-based projects have already shown positive impacts on undergraduate students' motivation, critical thinking skills, professional and technical skills, identity and self-efficacy, interpersonal skills, attitudes towards community service, and recruitment/retention (Astin et al., 2000; Bielefeldt et al., 2009; Coyle et al., 2003; Duffy et al., 2009; Fisher et al., 2005; Freeman, 2011; Harding et al., 2010; Lemons et al., 2011; Williams et al., 2009; Zarske et al., 2011). It is, then, reasonable to expect that approaches designed to retain undergraduate engineering students might also help in attracting K-12 students to engineering (Ohland et al., 2008).

In short, the use of developmentally appropriate engineering curricula that builds on current cognitive research and the success of hands-on, inquiry-based, and project-based instruction, coupled with a service context, becomes an attractive instructional option at the K-12 level. By experiencing the engineering design process early on in their educations, students begin to see how engineering advancements and innovations shape their everyday lives, and they begin to develop identities that open doors to technological or STEM futures. If we want U.S. engineering to continue to be globally competitive, then we must attract more students to its degree programs; especially students who represent the changing diversity of the U.S. college-aged population. The numbers of qualified and creative engineering graduates can only be boosted through increased interest of college-age students and higher retention rates through improved instructional methods and curricula once the students have matriculated.

Example K-12 Engineering Programs

Many K-12 engineering education initiatives implemented by U.S. universities and colleges have been well documented, providing us with descriptions of program logistics, partnerships, methods and curricula, as well as the impact on involved students, teachers and undergraduate and graduate students. The increasing number of members in the American Society for Engineering Education's (ASEE) K-12 and Pre-College Engineering Division, now ranked as the 12th largest division of 50, is a testament to the growing enthusiasm for formalized engineering partnerships in the K-12 arena. More than 120 technical conference papers on K-12 programs and partnerships were accepted and presented during the 2011 ASEE Annual Conference, further demonstrating the importance of collaboration and determination of best practices in K-12 engineering curricula, content delivery approaches, and teacher professional development. Examples of nine university engineering programs designed to impact K-12 student learning, K-12 teacher development, and K-12 student access are described below (in alphabetical order, by university).

1. *The College of New Jersey*—TCNJ developed an elementary education bachelor's degree in which students focus on math, science, or technology. Assessment of the degree program indicates an increase in the skills and comfort level of elementary teachers with STEM content knowledge. This program covers a breadth of STEM areas, and its graduates score higher on national math and science tests and equivalently on language and social studies compared to their peers. The research also indicates that the common STEM anxiety of K-12 teachers is lessened by participation in the program (O'Brien, 2010).
2. *Colorado School of Mines*—Colorado School of Mines studied the effectiveness of hands-on engineering activities tailored for middle school students that illustrate the relationship between mathematics and science. They engaged in several professional development projects to improve middle school teachers' understanding of mathematics and science, and the underlying relationship to engineering. They received a positive

response from workshop participants, and estimate the extended impact of the program reaches more than 5,000 students per year (Tafoya, Nguyen, Skokan, & Moskal, 2005).

3. *Colorado State University*—Colorado State University developed an engineering education degree path that culminates in both an ABET-accredited engineering science degree as well as experience and a recommendation for state teacher licensure in technology education. The students in this program complete degree requirements for both engineering and pre-service education, including traditional fundamental courses (calculus, physics, chemistry) and a semester-long student teaching or internship experience. Initial assessment indicates that the engineering-trained teacher candidates are successful in leading both theoretical and practical application lessons.
4. *Purdue University*—Purdue University developed and widely implemented their Engineering Projects in Community Service (EPCIS) program for the high school level. This service-learning program engages student engineering teams in authentic design for not-for-profit organizations in the local community. Their assessment concludes that EPICS helps dissolve engineering stereotypes and appears to attract a more diverse population to engineering opportunities, especially women (M. Thompson et al., 2008).
5. *Towson State University*—Pamela Lottero-Perdue at Towson State University implemented a summer engineering and science club at a Maryland Boys & Girls Club. Aimed at elementary aged-children, Lottero-Perdue used Engineering is Elementary (EiE) curricula from the Boston Museum of Science. The pilot program results suggest that these students collectively developed more sophisticated understandings and definitions of technology, including the ability to think critically about potentially

negative impacts for misuse of technologies as a result of participation in the six-week program (Lottero-Perdue, 2009).

6. *University of Colorado Boulder*—CU-Boulder's K-12 engineering education team examined 12 years of executing and refining a K-12 engineering education program within three varied school districts. Results indicated that involvement in the K-12 engineering education partnerships supports students' enrollment in more rigorous courses of study in high school and in many cases affected their college decisions (i.e., whether or not to pursue a collegiate engineering education); and ultimately, their career path (Zarske et al., 2007). Furthermore, engagement of high school students in a multi-year university sponsored program can also inspire allegiance to that university (Zarske et al., 2007).
7. *University of Massachusetts Lowell*—The University of Massachusetts Lowell implements several K-12 programs targeted on college access for middle school to high school student populations from backgrounds typically underrepresented in engineering. When students were surveyed after their engineering experiences, they indicated more interest in pursuing engineering/technology careers. Forty percent of students who were surveyed two-five years after their design summer camp experience indicated that the camp's exposure to engineering was a factor in deciding their career interests (Barrington & Duffy, 2007).
8. *Utah State University*—The National Center for Engineering and Technology Education (NCETE) at Utah State University is involved in research addressing the differences between high school students as novice designers in comparison with expert designers, or practicing engineering professionals. Leveraging on the work from the University of

Washington Center for Engineering Learning and Teaching, findings from their pilot study suggest that high school students spent more time in gathering information and project realization than the engineering experts (professionals) who spent more time in developing alternative solutions and feasibility (to be expected). They recommend that K-12 classrooms spend more time focused on modeling and decision making to support the learning of higher level problem solving skills (Mentzer & Park, 2011).

9. *Vanderbilt University*—Prior research shows that young women learn better when curricula are hands-on, link STEM to the real world, are collaborative, and utilize verbal skills. Based on that research, Stacy Klein and her group at the VaNTH Engineering Research Center for Bioengineering Educational Technologies studied the impact of curricular units modified to fit these characteristics and focused around a "grand challenge" (Klein & Sherwood, 2005). This small study compared students engaged in the new curricula to control groups in traditional physics classes and showed that the females in the experimental group outperformed their male counterparts on content knowledge questions while the females in the control groups did not (Klein & Sherwood, 2005).

Overall, these programs are a small sample representing the impacts of engaging K-12 students and teachers in pre-college engineering. They demonstrate the myriad benefits to both the in-service and pre-service teachers and budding students, including: increased awareness of the breadth of engineering disciplines, a deeper understanding of fundamental math and science concepts, more informed discourse on technologies in their everyday life, and ultimately, increased interest in engineering futures for students both traditionally and untraditionally attracted to the discipline.

Engineering is still far from being a standard in every K-12 school curriculum. In part, the lack of widespread implementation is due to the need for more research on the potential impact on students and teachers from engaging in engineering at the K-12 level, as indicated in *the Engineering in K-12 Education: Understanding the Status and Improving the Prospects* report (Katehi et al., 2009). Numerous types of interventions are possible, from formal to informal, aimed at students or teachers, and targeted on increasing interest or content skills. With such a variety, it is hard to determine what are best practices and why. A review of accepted conference papers to the ASEE K-12 Division in 2011 indicated many K-12 engineering program implementers do not understand what is involved in quality assessment and evaluation (Walden, Brown, & Zarske, 2011). Few programs use random-control methodology; some use quasi-experimental approaches with matched comparison groups, and most use pre- and post-assessments (Walden et al., 2011). Given the growing trends in K-12 engineering education and the demonstrated benefits from some K-12 engineering programs, it is imperative to increase quality research around the learning of engineering at the K-12 level to better determine the impact for evolving STEM instruction in K-12 schools and the best practices for implementation.

Assessment in Engineering Education

Assessment is a key component in evaluating the effectiveness of instructional methods and is necessary for creating curricular change in engineering education. In their 2005 *Journal of Engineering Education* article, Olds, Moskal, and Miller offer a helpful working definition for assessment. They define assessment as “the act of collecting data or evidence that can be used to answer classroom, curricular, or research questions,” while assessment methods are the procedures used in order to gather the assessment data (Olds, Moskal, & Miller, 2005). To be eligible for accreditation, engineering departments are required to conduct rigorous assessment of students.

Assessment Methods

Assessment methods are often divided into two categories: descriptive studies that describe the current state of a methodology and experimental studies that look at the changes that occur when a treatment methodology is used (Olds et al., 2005). Descriptive studies in engineering include methodologies such as surveys, interviews and focus groups, conversational analysis, observation, ethnographies and meta-analysis (Olds et al., 2005). Most commonly used, surveys are self-reporting instruments that can involve open-ended and multiple response questions to probe participants for personal feedback on the questions being researched. Two difficulties of surveys include poor response rate and participant candidness (Freedman, Pisani, & Purves, 2007; Olds et al., 2005). Interviews and focus groups involve personal dialogues with individuals to probe for feedback that captures data that cannot be observed. Again, candid answers from the participants can be variable in an interview. A focus group is similar to an interview, but involves a small group of people being interviewed at the same time as opposed to individuals. Other threats to validity in an interview or focus group can be a bias on the part of the interviewer or making sure the interviewer follows instructions (Freedman et al., 2007). Conversational analysis, observation, and ethnographies share time- and labor-intensive drawbacks and are less commonly used. Finally, in a meta-analysis, the researcher uses statistical techniques to broadly compare multiple studies that are addressing the same research question (Olds et al., 2005). One challenge to conducting meta-analyses is obtaining the complete data for each research study, since most publications of educational research report more positive results than negative results (Olds et al., 2005).

Experimental studies in engineering include methodologies such as randomized controlled trails, matching, baseline data, and longitudinal design (Olds et al., 2005).These methods all aim to quantify the impact of treatments or interventions an outcomes. For example, a randomized controlled experiment, the “gold standard,” compares the outcome of a control versus a treatment group in which subjects are randomly assigned to either the treatment or control group (Freedman et al., 2007; Olds et al., 2005). In engineering, this is often used when a new curriculum is introduced and the effectiveness is compared to the previous one (Olds et al., 2005). A randomized controlled experiment, if not designed properly, can encounter multiple confounding factors, or reasons that the effect is different than observed, that threaten the validity of the experiment (Freedman et al., 2007). If randomized controlled experiments are not possible, several quasi-experiments can be used. Examples of quasi-experiments include matching, or comparing the demographic data of students to show that the treatment and control groups are comparable, and baseline data, or the use of data that was collected before the treatment was implemented (Olds et al., 2005). A concern with baseline data is environmental and historical events that occur concurrently with the control group that actually cause the effect. Lastly, longitudinal designs measure the long-term impact of treatments. Longitudinal designs are challenging to implement in engineering education for several reasons, including attrition and inability to keep control and treatment groups distinct over time (Freedman et al., 2007; Olds et al., 2005).

CHAPTER III

RESEARCH OBJECTIVES AND HYPOTHESES

Research Objectives

Using a modified engineering design curriculum within a service-learning context enables students to practice technical and problem-solving skills while developing new skills associated with local community-based service. My primary research focus is on improving K-12 and first-year undergraduate student engineering design experiences to address the gap between the teaching practices of engineering education and the learning styles of today's engineering student population, based on current understanding of learning theory. My intention is to increase the base of practical knowledge available in the literature to researchers and educators interested in making improvements to the way engineering is taught in today's classrooms.

To date, very little previous work is available in the literature that compares project-based learning (PBL) to project-based service-learning (PBSL) to determine any specific psychological and educational benefits from engaging in service-learning. The service-learning projects for my research are intentionally selected to provide students with engineering design work that result in an improved quality of life or a higher standard of living for targeted local Colorado communities. In particular, I looked at developmentally-appropriate PBSL design projects that were integrated into sections of a *Creative Engineering Design* course at a partner high school as well as sections of the *First-Year Engineering Projects* course at CU-Boulder. These sections were compared to non-PSBL sections of the same course to observe any differences in participants' identity with engineering and attitudes towards community service. Specifically, the following research questions were proposed:

1. Does the engagement in PBSL projects impact students' identity with the engineering profession?
2. Do first-year undergraduate students engaged in project-based design during their first semester of study change their identity with the profession of engineering over time? Does a relationship exist between students' identity trajectory and a service-learning context, gender, and/or self-reported intent to continue in engineering?
3. Do high school students engaged in project-based design change their identity with the group of engineering students over time? Is there a relationship between students' identity trajectory and a service-learning context, gender, and/or ethnicity?
4. Does the engagement in PBSL projects impact students' personal responsibility towards community service?
5. Do high school engineering students and first-year undergraduate engineering students engaged in PBSL during their first semester of study develop a deeper awareness of the existence of needs in the local community and personal responsibility for helping the community?
6. Do high school students and first-year engineering undergraduates have differences in attitudes towards community service?
7. Does a relationship exist between students' community service attitudes and a service-learning context and/or gender?

Research Hypotheses

Based on the current literature around PBL design courses and service-learning in engineering, as well as preliminary research, I put forth the following hypotheses:

a. Engagement in PBSL positively impacts students' identity with engineering at both the high school and first-year undergraduate levels.

b. Engagement in PBSL does not differentially impact female students' identity with engineering compared to PBL at both the high school and first-year undergraduate levels.

c. Engagement in PBSL differentially impacts students considered minorities in engineering disciplines' identity with engineering at the high school level.

d. Engagement in PBSL develops a deeper personal responsibility towards community service among high school and first-year undergraduate engineering students.

e. Engagement in PBSL does not differentially impact female students' personal responsibility towards community service compared to PBL at both the high school and first-year undergraduate levels.

f. Engagement in PBSL has a larger impact on high school students' personal responsibility towards community service than first-year undergraduate students.

g. Some students in both high school and first-year undergraduate levels will start with a highly positive personal responsibility towards community service that will be maintained regardless of engagement or not in PBSL projects.

CHAPTER IV

IMPACTS OF SERVICE, GENDER, AND INTENT ON FIRST-YEAR ENGINEERING STUDENTS' DEVELOPING IDENTITY WITH ENGINEERING

Introduction

Declining retention rates of U.S. engineering students compared to overall college enrollment across the nation, coupled with a high global demand for qualified graduates and greater university accountability, continue to fuel engineering community concerns about the curricula and instruction in engineering institutions (Engineering Trends, 2008; Fortenberry et al., 2007; National Science Foundation, 2008). We are all aware of the looming challenge for this nation to keep pace with predicted future growth of the global science and engineering workforce when only 5% of U.S. college graduates major in engineering, compared to 20% of college graduates in Asia and 12% of European graduates (National Science Board, 2010a, 2010c). The National Academies' *Rising Above the Gathering Storm Two Years Later* publication (2009), reminds us that amidst a growing population of minority students, we are not attracting a diverse population into STEM undergraduate programs (National Research Council, 2009). The numbers of qualified and creative engineering graduates must be boosted through increased interest of college-age students and higher retention rates for engineering undergraduates, which may be realized via improved instructional methods and curricula.

One popular curricular intervention is the integration of project-based design experiences throughout the undergraduate engineering curriculum. Proponents contend that project-based courses should be offered early in students' undergraduate career for a variety of reasons. The design aspect of hands-on project-based courses offers a rich learning environment that enables freshmen to “become” engineers right away instead of waiting until their junior or senior years; and we know this can help increase confidence, skills mastery, and student retention (Carlson & Sullivan, 2004; Constans & Kadlowec, 2011; Olsen & Washabaugh, 2011).

Paretti & Cross (2011) conducted an extensive literature review of first-year engineering programs and found that experiences varied from small-scale to large-scale projects, spanning one semester to a full year. They summarized 50 programs reported in the literature during the last five years and—not surprisingly—found that assessment generally fell into two categories: retention (including attitudes, motivation) and design skills (Paretti & Cross, 2011). Across the programs, they also noticed very few similar measures of outcomes to describe success. The large number of papers written about first-year programs is testament to the importance and enthusiasm of engineering educators for improving student experiences, but a strong community of sharing and assessment is an essential missing piece (Paretti & Cross, 2011).

Service-learning projects—an educational method through which students actively participate in community service as an integral component of their coursework—are another popular curricular reform. Often in combination with project-based design, courses that emphasize engineering for social good are reported to be highly motivating for students to study engineering, and have a positive impact on student recruitment and retention (Coyle et al., 2003; Sheppard et al., 2010; West et al., 2010). Researchers have repeatedly asked if real-world problems or service-learning context increase students’ connection with the profession of engineering and thus increase their intent to find a career in the field (Bielefeldt et al., 2009; Harding et al., 2010; B. D. Jones et al., 2010). While significant publications on the effects of mentoring, design, and discipline-specific projects on first-year students have been shared, most researchers agree that a greater understanding of first-year programs is necessary to deeply comprehend the factors at play in the retention of capable and interested students (Meyers et al., 2010; Paretti & Cross, 2011).

For this paper, we closely examine a project-based engineering design course and student perceptions in the first-year engineering program at a large public university. We observe the change in attitudes for undergraduate engineering students engaged in project-based design during their first semester of study and whether a service-learning context, gender, and/or intent to continue in engineering impact this change trajectory. We assimilate our results to offer insight into the dynamic attitudes of identity in a cohort of first-year engineering undergraduate students at the University of Colorado Boulder.

Related Literature on First-Year Project-Based Courses, Service-Learning, and Identity

Research on knowledge acquisition indicates that educating students using active, inquiry-based learning approaches in which they discover how to identify problems, assimilate new information, evaluate alternative solutions, and reflect on their own cognitive development, helps students extrapolate solutions to different settings (Brophy et al., 2008; Pellegrino, 2002; Prince, 2006). Thus, the ability for students to transfer the knowledge learned in the classroom to the professional world is more likely to develop when a course context mimics a real-world setting.

A review of the current literature provides strong support for hands-on, project-based engineering design experiences as an instructional method to improve student knowledge and attitudes towards engineering. Project-based learning (PBL) has become popular as a result of cognitive development research in neuroscience and psychology. This research proposes two concepts: 1) learning is partly a social and cultural activity and 2) learners use their prior knowledge to explore, construct, and create new knowledge (Markham et al., 2003). In general, research around the effectiveness of PBL suggests that it creates a motivating environment for the teaching of basic skills, and increases students' perceived connections between theory and practice, exhibition of professional skills at high levels, ability to transfer skills to other situations, and encourages habits of mind that lead to lifelong learning and career success (Markham et al., 2003; Prince, 2006; Windschitl, 1999). Students engaged in PBL perceive more support from their instructors, while instructors of PBL report an improved contentment with teaching, improved quality of interaction with students, and an increase in student competencies (Prince, 2006). Drawbacks to PBL include the impacts of unbalanced team participation and the time and effort required to complete projects—both issues commonly faced with group projects (Prince, 2006).

Often team-based in nature, first-year engineering PBL courses have resulted in increased gains in knowledge across genders and can be effective in increasing students' self efficacy and confidence in using the engineering design process (Constans & Kadlowec, 2011; Harding et al., 2010; Olsen & Washabaugh, 2011; Sheppard et al., 2010). This is impactful, especially in light of the results from the prominent APPLES study that concluded that first-year students tend to enter their engineering courses already highly confident in three areas: their abilities to solve open-ended problems; math and science knowledge; and professional/interpersonal skills (Sheppard et al., 2010). For women, who may rate their knowledge and design skills lower at the beginning of their first-year PBL experiences, Knight et al. (2003) reported a closing of the gender gap on those skills by semester-long course end (Knight et al., 2003).

Other research indicates that instruction in service-learning (SL) centered experiences can improve academic learning of material and provide participants with a deeper understanding of the social context of their work, increasing technical, professional, and interpersonal skills (Astin et al., 2000; Bielefeldt et al., 2009; Jacoby & Associates, 1996; Lemons et al., 2011; Lima & Oakes, 2006; Zarske et al., 2011). In this context, community needs define the service tasks and provide students with a sense of responsibility for being members of a larger community (Jacoby & Associates, 1996).

Many SL courses and programs report a higher female participation, indicating that women are generally more inclined towards SL and volunteer to participate in SL at a higher rate than their male counterparts (Bielefeldt et al., 2008; Coyle et al., 2003; Duffy et al., 2009; Freeman, 2011; Matusovich et al., 2006; Mihelcic et al., 2008; Seider et al., 2011). For example, in 2007, Engineers Without Borders (EWB)—a SL organization whose mission is to partner with disadvantaged communities to improve their quality of life while developing internationally responsible engineering graduates—had equal or higher representation of women in leadership positions in 23 of 24 established chapters in the United States (Zimmerman & Vanegas, 2007). Often combined with project-based learning to form project-based service-learning (PBSL), learning through service is still not universally integrated throughout engineering education curricula, and a majority of SL in engineering is limited to senior capstone courses and extracurricular offerings (Bielefeldt et al., 2010; Freeman, 2011; Moskal et al., 2008; Tsang, 2000c).

In first-year programs, PBSL has specifically been reported to positively impact students' perceptions of their roles as engineers, awareness of socially responsible opportunities, and satisfaction with the first-year-experience (Coyle et al., 2003; Freeman, 2011; Harding et al., 2010). Unfortunately, little previous work is available in the literature that compares PBL to PBSL to determine any specific psychological and educational benefits from engaging in service-learning.

PBSL in engineering courses is embodied within the construct of situated learning theory, centered on the idea that whatever is present in the environment during learning becomes part of what is learned. In other words, learning engineering is learner-centered, placing students within a context and learning community in which they actively participate in the learning process (J. S. Brown et al., 1989; Lave & Wenger, 1991). PBSL problems, similar to situated learning problems, are considered more motivating to students because they solidify the connections between real-world applications and what they are learning (Bielefeldt et al., 2009; Svinicki, 2008).

Situated learning and PBSL also both contribute to the formation of identity with the engineering profession for students (Bielefeldt et al., 2009; Stevens et al., 2008). Identity with a profession—or the type of person that one is currently or desires to be, as viewed by both the self and perceptions of others—is a complex process that develops over time and includes shared attitudes, knowledge, and skills characteristic to a member of that profession (K. Adams et al., 2006; Beam et al., 2009; Matusovich et al., 2009). Thus, as students are learning to become engineers, they are concurrently impacted by the learning activity, the context, and the culture — all of which collectively shapes their engineering identities. A student's perception of being part of an engineering discipline and how much of the student's self is intertwined with the engineering discipline can influence post-graduation career choice (Matusovich et al., 2011; Plett et al., 2011).

Mixed results are found in describing differential effects of identity development by gender. While the Academic Pathways Study (APS) suggests that pathways to engineering identity do not vary considerably by gender or ethnicity, other research suggests that engineering identity does vary over time by gender (Atman et al., 2010; Beam et al., 2009; Chachra et al., 2008; Pierrakos et al., 2009). The slowly growing body of research on identity and service-learning indicates that participation in academic SL courses leads to significant and enduring increases in identity (Batchelder & Root, 1994; S. R. Jones & Abes, 2004). Unfortunately, these studies were conducted with undergraduate students in liberal arts and education majors; no reported research exists on whether the opportunity to engage in engineering for “social good” specifically increases engineering identity.

Several programs report that participation in SL positively impacts students’ determination to continue in engineering (retention) or was a factor in program selection (recruitment) (Coyle et al., 2003; Duffy et al., 2009; Fisher et al., 2005; West et al., 2010). The belief that engineers contribute to improving society, or engineering for a social good, seems to resonate with a diverse group of students throughout the literature. Even though Bielefeldt (2008) discovered few significant differences in the self-reported attitudes towards community service of the SL students based on gender (e.g., connectedness to the community and career benefits of helping), it also appears that females are more likely to agree that SL helped keep them in engineering (Bielefeldt et al., 2008; Duffy et al., 2009).

It is conceivable that a first-year PBSL course offers an opportunity to immerse students in hands-on engineering design for a specific or theoretical client, demonstrating the usefulness of the trade in a concrete way. This is supported by University of Colorado Boulder research on the retention and graduation of engineering students who had exposure to hands-on design courses in their freshman year of undergraduate study. This research shows an overall 64% retention rate into the seventh semester of students enrolled in the course compared to a 54% retention rate of students who did not enroll in the course, with an even higher overall retention of women and African American students (67% and 70%, respectively) (Fortenberry et al., 2007;

Knight et al., 2007). The overall graduation rate of engineering students engaged in hands-on design courses during their freshmen year is 62% compared to 52% graduation rate for students who did not enroll in the course (cumulative over 11 years of data), with an even higher overall graduation rate of women students at 64%.

Research Questions

This study examines first-year engineering projects students' perceptions on outcome variables previously described in the literature, particularly identity with the engineering profession. Specifically, we explore the following research questions:

1. Do engineering undergraduate students engaged in a project-based design course during their first semester of study change their identity with the profession of engineering over time?
2. Does a relationship exist between students' identity trajectory and a service-learning context, gender, and/or self-reported intent to continue in engineering?

Methods

Setting

The setting for the implementation of our research questions is the *First-Year Engineering Projects* (FYEP) course that has been evolving over the last fifteen years at the University of Colorado Boulder and described in previous papers (Knight et al., 2007; Zarske, Reamon, Bielefeldt, & Knight, 2012). This introduction to engineering course offers students an interdisciplinary, hands-on design-build experience and includes extensive training in team dynamics, communication, and time management skills. Student teams design and create prototype engineering products that are displayed and judged at an end-of-semester design expo for their peers and the public. The products, ranging from more theoretical design such as toys and Rube Goldberg machines to assistive technologies with actual clients, are chosen by the individual professors and differ across the course sections. The three-credit, one-semester course serves ~450 first-year students annually in sections that cap at 32 students.

The FYEP course is committed to rigorous assessment and evaluation of educational outcomes and changes in students' attitudes. Most students who take the FYEP course (~70%) do not volunteer to take it, but complete it as a departmental requirement for certain engineering majors. Students majoring in mechanical, environmental, and aerospace engineering are required to take this course, while civil engineering and "undecided" majors are strongly encouraged to take it during their first semester, according to online advising guides. When choosing a section in which to enroll, students only know which professor is teaching the section, as listed in the university course catalog; they are not aware of the specific design project their team will complete. Engineering students who are required to take the course do not characteristically enroll with a professor from their department or major, resulting in sections filled with a mix of students from different engineering disciplines.

Participants

The analysis in this report contains survey data from 272 FYEP engineering students enrolled in 10 sections of FYEP during the fall 2010 semester (38% of the 2010 incoming first year engineering class); 20 students were eliminated from the study due to absences during either the pre- or post- survey. Participants included 25% females (n=68) and 75% males (n=204), which is slightly higher representation than the 24.2% females in the overall incoming freshmen engineering class. Most were first-year students (N=252), with a few sophomores (n=13) and upper class students (n=7). Most engineering majors offered at the university were represented, with students indicating aerospace (n=60), architectural (n=10), chemical and biological (n=16), civil (n=39), electrical (n=11), environmental (n=42), and mechanical (n=40) as their major of most interest at the semester start. Half of the course sections (*n*=5) were challenged with service-learning projects and the other half (*n*=5) engaged in non-service-learning design projects (see Table 4.1). Ten professors instructed the ten sections, with one professor teaching two sections and two professors co-teaching one section.

Table 4.1. Section topics for the fall 2010 semester offerings of FYEP, divided by service-learning and non-service-learning

Service-Learning Topics	Non Service-Learning Topics
Section 2: Assistive Technology	Section 1: Rube Goldberg Machines
Section 3: Assistive Technology	Section 4: Robotics
Section 5: Assistive Technology	Section 6: Water Systems
Section 8: Local Community Products	Section 7: Green Design
Section 10: Health Games	Section 9: Robotics

Assessment Instrument Design

Students participated in a voluntary, in-class, online engineering attitude survey during the first week of the fall 2010 semester (pre) with choices on a five-point Likert-type scale ranging from "not at all" to "definitely." They completed the same survey at semester end (post), 15 weeks later, to measure any changes in student attitudes towards engineering as a result of exposure to their first semester of engineering undergraduate experiences including the FYEP course. Students typically completed the survey instrument within ~15 minutes. Survey questions that related to the goals of this study were adopted from previously developed undergraduate engineering surveys and integrated into the college's existing FYEP course survey, including:

- The Persistence in Engineering Survey (PIE), which includes measurements of students' self-estimates of technical skills and professional skills related to engineering design work (source of 26 items) (Eris et al., 2010).

- The Community Service Attitudes Scale, which assesses the degree of participants' attitudes regarding community service (source of 15 items) (Shiarella, McCarthy, & Tucker, 2000).
- The Engineering Identity Survey developed by Chachra et al., which assesses the degree of participants' group identification with engineers (source of 11 items) (Chachra et al., 2008).
- Conceiving Designing Implementing Operating (CDIO) Initiative student skills survey, which measures student confidence in their abilities to perform an engineering design-centered task (source of 33 items) (Crawley, 2001).

These items comprised the dependent variables in this study (N=85). Additional Likert-type questions were asked of the students, including their intent to complete a major in engineering, and their self-perception of their knowledge of engineering pre- and post- semester. In addition, demographic data such as gender, ethnicity, and year were collected, with missing values retrieved from the university student data system. Overall instructor ratings from the college's end-of-semester faculty course questionnaires, type of project for each section, and student retention into the second year of engineering were collected and added to the dataset as they became available. Surveys for all participating students are conducted under the University of Colorado Boulder's Institutional Review Board (IRB) approval, reviewed annually by external and internal evaluators. Student responses were coded to protect participant identity.

The quantitative survey items, coupled with qualitative answers to open-ended survey questions, cumulatively query students' changing attitudes over time. Since the items adopted from the PIE survey measure both technical skills and professional skills, theory suggests that the FYEP survey measures five separate constructs: student perceptions of their technical skills related to engineering, student perceptions of their professional skills related to engineering, confidence in engineering, identity with the engineering profession, and attitudes towards community service.

The validity of our instrument was examined to determine how well the items measure the five intended constructs. The 85 items had an internal reliability using Cronbach's Alpha of 0.97 (a value exceeding 0.7 is considered adequate) (Nunnally, 1978). High inter-item reliabilities suggested that the survey items could also be reduced to a smaller number of associated factors through factor analysis. A Principal Components Analysis (PCA) was performed on the sample to analyze the theoretical constructs represented by the sets of survey response items related to identity, technical skills, professional skills, confidence, and community service. The number of factors was determined by examining the total variance explained, as well as a Cattell's Scree test, which takes independent weighted combinations of the original questions (those combinations that correspond to the resulting factors) and places them in serial order of greatest variance to least variance. The Scree test then plots the variances of the factors against their serial order and helps determine where the major change of variance drops off. In this analysis, the Scree plot suggested a five- or six-component solution. PCA was re-run using both five and six dimensionalities and the results were compared. As very little explanatory power was added by including a sixth dimension, a five-factor solution was chosen (see Appendix A for total variance explained). PCA suggested that both professional skills and identity may correlate with students' confidence in engineering though not as strongly with each other (see Appendix A for component correlation matrix). The averages of the items that loaded on a given factor were used as dependent variables in the reminder of this analysis.

Variables in this Analysis

Many different variables are necessary to examine the longitudinal change in perceptions and attitudes of engineering students in the FYEP course. Other courses and experiences outside FYEP could impact these perceptions and attitudes. However, most first semester students, regardless of major, take a similar roster of courses (calculus, calculus-based physics or chemistry for engineers, a one-credit introduction to engineering course, and a social-science or humanities elective).

The dependent variables for this analysis to potentially explain the variation in attitudes and perceptions between student groups were selected on the basis of empirical research on service-learning and hands-on projects and confirmed through reliability analysis. While many combinations of independent and dependent variables could be examined from this data set, this paper focuses on the *student perception of identity* with the profession of engineering (11 items). Example survey items for the factor of identity are presented in Table 4.2.

Table 4.2. Survey Items for *Identity* in the FYEP Survey

Factor, Number of Questions, and Example Constituent Items
Identity (11 items) (Chachra et al., 2008) How much do you agree with the following statements *In general, being an engineering student is an important part of my self-image.* *I fit in well with the other engineering students in the College of Engineering.* *I have a strong sense of belonging to the engineering student community.* *Being an engineering student is an important reflection of who I am.*

The identity factor was rated by students on a five-point Likert-type scale ranging from “not at all” to “definitely.” The data reduction combined the student responses to the identity items into a single average identity score. Other variables collected for this analysis include enrollment in a service-based section of the course (treatment), the demographic variable of gender, and intent to complete a major in engineering. Analysis outcomes with significant findings are discussed below.

Statistical Analysis

The average of the 1-5 Likert- scale responses that loaded on the identity factor is used to represent the dependent variable. For example, a higher average of the pre-survey item scores for identity indicates a student's greater initial overall perception of their identity with the profession of engineering. Next, this variable was paired pre- to post- for each individual.

First, we analyzed the data for missing values and data entry errors. Twenty students who did not complete either a pre- or post- survey were excluded from the data set prior to analysis. Any missing values were examined for patterns, and no student skipped more than one or two items in each administration of the survey. Missing survey data was handled during subsequent analyses with listwise deletion. Missing demographic data was retrieved from the university student database.

A repeated measures of analysis of variance (ANOVA) was used to examine within-person and between-groups relationships of the overall FYEP course by section. This enabled us to find any differences by section that would justify class-level examination of the data. The ANOVA confirmed within subject and between group differences across course sections for each variable. As a result, each variable is subsequently examined by class differences, differences between students within classes, and students' differences over time. For these analyses, IBM SPSS statistical software package (version 20) was used.

Developing a Multilevel Model for Change to the Data

Our data includes both variables that describe individuals and variables that describe groupings of individuals, common to education research. Next, we developed a model to estimate both course- and individual-level effects on our outcomes and relationships of interest. Traditional regression does not effectively model nested systems, since it assumes that all effects occur at either the individual or group level. The type of complex systems model for the FYEP data can be better represented using a multilevel model, such as hierarchical linear modeling (HLM). HLM allows the researcher to represent the relationships between variables on one level (such as individual-level) while also considering the influence on relationships at another level (such as course-level) (Raudenbush & Bryk, 2002). Education researchers often use HLM in the development of models in which the independent variables are on multiple levels (individual, course, or school), and the dependent variable is at the lowest level of analysis (Borchers & Sung Hee Park, 2011).

Model specification began with an inspection of empirical growth plots and superimposing fitted OLS-estimated linear trajectories for individual subjects. The resulting plot suggested inter-individual heterogeneity in change, and a general pattern emerges. For the entire study population, participants either increase or decrease their identity with engineering over time, with an average of no change for the population as a whole. This suggests a need for further modeling with viable predictors of change.

Next, a level-1 model was hypothesized that can describe the intercept and rate of change for an individual within the FYEP course. In other words, for this population, the dependent variable of identity was considered a linear function of individual *i*'s TIME on occasion *j*. Time was centered on the first occasion in which the data was collected (TIME 0) in order to facilitate interpretation of the intercept. The level 2 model represents the hypothesized effects on how the level-1 individual growth parameters are related to between-subject factors, such as service and gender. To develop level 2 models, the level-1 individual growth parameters of true initial status

(π_{0i}) and true rate of change (π_{1i}) were used as outcomes, creating two level 2 sub models for inter-individual differences in change. These level 2 models speculate the existence of an average trajectory of the population for each between-subject factor. The level 2 residuals account for each individual's own true change trajectory (defined by π_{0i} and π_{1i}). Regression analyses were conducted to examine the relationships between the dependent variable, participation in service-based sections of the course, gender, and students' intent to complete a major in engineering.

To find the best values for parameter estimates, a full maximum likelihood (FML) estimation method was utilized. FML estimation provides estimates for values of unknown population parameters that maximize the possibility of observing the specific data sample. FML estimates have distinct advantages in large random samples; they are unbiased (consistent), approximately normally distributed with known variance, and efficient (Singer & Willett, 2003). The resulting estimates contain all of the fixed effects as well as the variance components from the model, and therefore describe the fit of the entire model.

A FML estimate of the data was completed using Hierarchical Linear and Nonlinear Modeling (HLM) software, a modeling software distributed by Scientific Software International, Inc.("Hierarchical Linear and Nonlinear Modeling (HLM)," 2011). A function describing the likelihood of seeing the data (using an unconditional means model and an unconditional growth model, described below) is run before multiple variables for population parameters are included to see which would most likely generate the sample data.

These analyses were somewhat exploratory in nature. We investigated several interrelationships between variables, and tested several combinations that do not appear in our final paper because they did not add to the overall strength of the models. In other words, some models did not offer significant regression coefficients or predict significant changes in pseudo-R^2 statistics and goodness-of-fit for these analyses.

Results

Overall Course

The survey results reported in this paper are from matched pre- to post- surveys of 272 students enrolled in 10 sections of FYEP during the fall 2010 semester at the University of Colorado Boulder. Initial data screening generated descriptive statistics that showed trends for the overall cohort of students (see Table 4.3). A paired-samples t-test was used to analyze the within-person differences in factor scores over the course of the semester. The resulting paired sample correlations indicate that students who scored higher on the pre-survey also scored higher on the post-survey.

The pre- to post-mean scores of the overall FYEP students, as shown in Table 4.3, demonstrate no significant change in identity for the overall students in FYEP and a significant decrease in intent to complete major, confirming what we saw in the individual trajectories. This cohort of FYEP students displays a moderate initial level of identity, with little variation in initial or ending identity score by gender or enrollment in a SL-section of the course. The students also start with a high intent to complete a major in engineering and slightly decrease in that factor over time, which is consistent with the APPLES study that demonstrates high initial confidence and self-perceived abilities in engineering and the findings by Seymour and Hewitt that report a loss of interest in engineering as the #1 ranked factor, contributing to the decision to leave an engineering major (appearing in 50% of research subjects who left engineering) (Seymour & Hewitt, 1997; Sheppard et al., 2010). The pattern continues for both genders and students in all sections of the course (SL and non-SL). It is interesting to note a fairly high standard deviation with respect to the question, “Do you intend to complete a major in engineering?” on the post-survey administration (1-5 Likert scale), indicating a large variability within these individual responses.

Table 4.3. Descriptive statistics for *Identity* in overall cohort of FYEP students

				Pre Survey	Post Survey	
Variable	**N**	**Min**	**Max**	**Mean (SD)**	**Mean (SD)**	**Mean Difference**
Intent to complete major	**269**	**1**	**5**	**4.46 (0.68)**	**4.32 (0.93)**	**-0.14***
Female	68			4.35 (0.69)	4.19 (.95)	**-0.16**
Male	204			4.50 (0.68)	4.37 (0.92)	**-0.13***
Service-learning project	139			4.54 (0.64)	4.30 (0.89)	**-0.24***
Non-service learning project	133			4.39 (0.72)	4.35 (0.97)	**-0.04**
Identity	**272**	**1**	**5**	**3.88 (0.55)**	**3.88 (0.67)**	**0**
Female	68			3.95 (0.44)	3.89 (0.63)	**-0.06**
Male	204			3.86 (0.58)	3.88 (0.68)	**0.02**
Service-learning project	139			3.90 (0.54)	3.91 (0.54)	**0.01**
Non-service learning project	133			3.86 (0.56)	3.86 (0.68)	**0**

Notes: Cell entries contain mean scores and standard deviations for student participation in the First-Year Engineering Projects course, by gender and service-learning context.
*Significant at the $p<0.05$ level, paired t-test

Unconditional Model Analysis

First, an unconditional means model (Model A) was fit to the data that quantified the identity outcome variation across participants without regard to time (see Table 4.4). This model helps determine if enough variation in intercept exists to warrant further investigation. The estimated average elevation of the true individual change trajectories for identity at the beginning of this analysis differed significantly from 0 (β_{00} = 3.88; p<0.001), leading to rejection of the null hypothesis of Model A and confirming that the score across participants is non-zero.

Table 4.4. Estimates of the fixed-effects of intercept and slope (β) and variance components (σ) from various models of inter-individual differences in *Identity* scores (IDY) in 272 participants over the course of the study, with standard deviations in parentheses.

			Model A Unconditional Means	**Model B** Unconditional Growth	**Model C** Growth by Section	**Model D** Growth by Service	**Model E** Growth by Gender	**Model F** Growth by Intent	**Model G** Growth by Service & Gender	**Model H** Growth by Service & Intent
Initial Status, π_{0i}	Intercept		3.88***	3.88***	3.91***	3.86***	3.86***	2.52***	3.86***	2.67***
		β_{00}	0.03	0.03	0.07	0.05	0.04	0.28	0.06	0.39
	Section				-0.01					
		β_{01}			0.01					
	Service					0.04			0.00	-0.35
		β_{02}				0.07			0.08	0.51
	Gender						0.09		0.01	
		β_{03}					0.08		0.10	
	Intent							0.31***		0.27**
		β_{05}						0.06		0.09
	Service* Gender								0.17	
		β_{06}							0.13	
	Service* Intent									0.08
		β_{091}								0.11
Rate of change, π_{1i}	Intercept			0.00	-0.05	-0.01	0.02	0.45*	0.01	0.15
		β_{10}		0.03	0.07	0.05	0.04	0.20	0.06	0.26
	Section				0.01					
		β_{11}			0.01					
	Service					0.01			0.01	0.68~
		β_{12}				0.07			0.08	0.41
	Gender						-0.07		-0.06	
		β_{13}					0.08		0.12	
	Intent							-0.10*		-0.03
		β_{15}						0.04		0.06
	Service* Gender								-0.03	
		β_{16}							0.16	
	Service* Intent									-0.15
		β_{20}								0.09
Variance components										
Level 1:	Within person, ε_{ij}		0.16*	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		σ^2_ε	0.01							
Level 2:	In initial status, ζ_{0i}		0.21	0.30	0.30	0.30	0.30	0.26	0.30	0.26
		σ^2_0	0.46	0.03	0.03	0.03	0.03	0.02	0.03	0.02
	In rate of change, ζ_{1i}			0.33	0.33	0.33	0.33	0.32	0.33	0.32
		σ^2_1		0.03	0.03	0.03	0.03	0.03	0.03	0.03
	Covariance between ζ_{0i}			-0.09	-0.09	-0.09	-0.09	-0.08	-0.09	-0.08
		σ_{01}		0.02	0.02	0.02	0.02	0.02	0.02	0.02
Pseudo R^2 Statistics and Goodness-of-Fit										
	R^2_ε			1.00	1.00	1.00	1.00	1.00	1.00	1.00
	R^2_0				0.00	0.00	0.00	0.13	0.00	0.13
	R^2_1				0.00	0.00	0.00	0.03	0.00	0.03
	Deviance		905.70	890.39	889.73	889.93	888.70	848.33	886.96	845.90
	AIC		911.70	900.39	903.73	903.93	902.70	862.33	908.96	867.90
	BIC		1204.52	1328.16	1419.02	1419.22	1417.99	1377.62	1539.19	1498.13

~p <0.10; * p <0.05; ** p <0.01; *** p <0.00

Also, the unconditional means model demonstrated significant difference from zero ($p<0.001$) for each variance component, which supports the possibility of linking the within-person and between-person variation in score to other predictors. From the unconditional means Model A, we conclude that the score varies over the duration of the study and that the individuals differ from each other.

Next, we fit an unconditional growth model (Model B), adding a predictor variable of *TIME* into the model and examining the individual elevation and linear rates of change (slope) for identity upon each participant's entry into the study. This model is a baseline model for change over time and differs from the unconditional means model by examining the scatter of each person's scores around his/her linear change trajectory instead of his/her mean intercept with an assumed flat trajectory as in Model A. The estimated average elevation of the individual growth in identity at the beginning of the study for the unconditional growth model differed significantly from 0 ($\beta_{00} = 3.88$; $p<0.001$), leading to rejection of the null hypothesis in the unconditional growth trajectory and suggesting that the true individual change identity trajectory has a non-zero intercept. The variance in initial status confirmed significant variability for prediction at level 2 in subsequent models. The estimated rate-of-change, however, was 0, suggesting, similar to the pattern in Table 4.3, that change over time is not immediately evident in the data. The level 2 variance component associated with rate of change was statistically significant, suggesting that certain amounts of variation in change could potentially be predicted with the addition of other variables into subsequent models.

It is important to note that these two models are successive; the variance components of the unconditional growth model cannot be directly compared to the variance components of the unconditional means model because the addition of the variable *TIME* changes the interpretation of the output.

Conditional Models Analyses

Next, we wanted to determine the effect of predictor variables of enrollment in a service-based section of the course (treatment), the demographic variable of gender, and intent to complete a major in engineering as predictors of both initial status and change. We examine these predictors in order to explain any between-person variation in each individual elevation (intercept) and linear rate of change (slope) seen in the unconditional models. Table 4.4 includes the estimates from these subsequent "fitted" models. While each independent variable along with variable interactions were modeled for predicted impacts on students' identity with engineering as a profession, only the models that included intent and intent with service context practically or significantly added to the overall strength of the analysis. These models (F and H) are covered in more detail in the rest of this paper.

Model F: Intent to Complete a Major in Engineering Over Time

$$IDY_{ti} = \beta_{00} + \beta_{05}*INT_i + \beta_{10}*TIME_{ti} + \beta_{15}*INT_i*TIME_{ti} + r_{0i} + r_{1i}*TIME_{ti}$$

Where parameters include:

- *IDY* is *Identity*, the level 1 outcome score of interest (on a scale of 1-5) of individual i (i=1 to 272) at time t (t= 0 to 1);
- *INT* is *Intent to Complete a Major in Engineering,* a level 2 time-variant predictor of subject study group (on a scale of 1-5);
- *TIME* is the time at which assessment t of subject i took place, administered pre- and post- semester and *centered* for each subject's entry into the study at time 0

- β_{00} is the population average of the level-1 intercepts for individuals with a level-2 predictor value of 0, or population average true initial status for nonparticipants;
- β_{05} is the population average difference in level 1 intercepts, β_{00}, for a 1-unit difference in the level-2 predictor *Intent*, or the initial impact of predictor *Intent* on initial status;
- β_{10} is the population average of the level 1 slopes, for individuals with a level-2 predictor value of 0, or population average rate of change for nonparticipants;
- β_{15} is the population average difference in the level-1 slope, β_{10}, for a 1-unit difference in the level-2 predictor, or the impact of predictor *Intent* on the individual rates of change;
- r_{0i} and r_{1i} are the level-2 residuals that represent those portions of the level-2 outcomes that remain unexplained by the level-2 predictors and are assumed to be drawn from a bivariate normal distribution with mean vector 0 and unstructured error covariance matrix. The level-2 individual variances in *true intercept* and *true slope* across all individuals in the population are represented by σ^2_0 and σ^2_1, respectively, and their covariance represented as σ_{01}.

This level-2 model speculates the existence of an average trajectory of the population for each *Intent* (on a scale of 1-5). However, the level-2 residuals account for each individual's own true change trajectory (defined by r_{0i} and r_{1i}).

In Model F, all estimations are based on a 1-5 Likert-style continuum from response score on *Intent*. The estimated initial score on *Identity* for participants who indicate a low intent to complete a major in engineering is statistically significant at $\beta_{00} = 2.52$, $p<0.001$. The estimated differential in initial *Identity* score between low and high intent participants is significant $\beta_{05} = 0.31$, $p<0.001$. The estimated predicted rate of change in *Identity* score for participants with low intent increases per time measured $\beta_{10}= 0.45$, $p<0.05$. Lastly, the estimated differential in the rate of change between low and high intent decreases by -0.10 points per time measured (β_{15}=-0.10), indicating that the model predicts participants with high intent decrease their *Identity* scores at the same rate as their peers.

This model shows that participants who indicated the highest intent to complete majors in engineering (on a 1-5 scale) started at a higher intercept for identity (0.31 points) than their peers with low intents. Students who indicate lower intents to complete an engineering major have a predicted increase in *Identity* over time (0.45 points per time), while their peers who indicate the highest intent scores have a predicted slight decrease in *Identity* score over time (by -0.10 points per time) . The differences in intercept are considered statistically significant at p<0.001, while the differences in rate of change are considered statistically significant at p<0.05. Figure 4.1 shows a graph of prototypical values for Model F, with initial intent scores of 2, 3, and 4, representing low, medium, and high intent, respectively, as determined by the empirical middle of students scores.

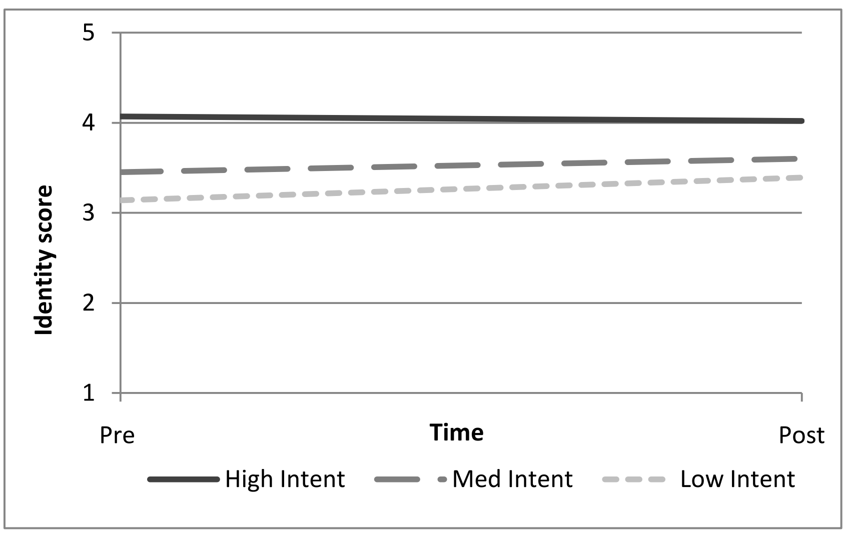

Figure 4.1. Prototypical change trajectories recovered from the HLM analyses for *Identity* score in 272 subjects by intent to complete majors in engineering. Time is reported in test administration.

In order to confirm the pattern in Figure 4.1 and find the overall decreasing pattern from Table 4.3, we took a closer look at the individuals in the FYEP cohort of students. The individual graphs of changing identity over time indicate large individual variation within groups of students with varying initial identity scores. Also, the greatest decreases seem to occur in students who ranked their *Intent* close to 4 on their initial survey. A residual file was created and analyzed in SPSS. Empirical Bayes estimate for standard deviation of time were highest for the group that ranked their *Intent* close to 4 (SD = 0.58), suggesting that the variability in slopes is greatest for this group. An examination of the sum of the fitted and residual (EC) correlation for the cohort was negative for all students, offering a pattern of highest growth greatest for those students with the lowest initial *Identity* scores. To mitigate the impact of the ceiling effect, we compared a restricted range of students who had initial pre-survey *Identity* scores between 3 and 4. This range was selected to remove the highest-scoring students and therefore make the analysis more sensitive to scaling issues, as well as to focus in on students without initially high identities who we most want to reach. The correlations for the smaller group of students were even lower, indicating that the students in the "middle" (n=149) grew differently than the entire group (N=272). In comparing the means of the restricted set, the group who initially ranked their *Intents* at 3 had slightly higher relative slopes than those who initially ranked their *Intents* at 4, suggesting that the lower-scoring students increased their identities at very slightly greater rate over time.

Model H: Service, Intent, and Interaction Over Time

$$IDY_{ij} = \beta_{00} + \beta_{02}*SERV_i + \beta_{05}*INT_i + \beta_{091}*SERV\_INT_i + \beta_{10}*TIME_{ti} + \beta_{12}*SERV_i*TIME_{ti} +$$

$$\beta_{15}*INT_i*TIME_{ti} + \beta_{119}*SERV\_INT_i*TIME_{ti} + r_{0i} + r_{1i}*TIME_{ti}$$

Where new parameters include:

- SERV is *Service*, a level 2 time-invariant predictor of subject study group (0=not SL and 1= SL section);
- SERV_INT, a level 2 time-invariant predictor that represents the interaction between *Service* and *Intent*.

This level 2 model speculates the existence of an average trajectory of the population for each combination of *Intent* (self-reported on a scale of 1-5) and *Service* (SL and non-SL sections). However, the level 2 residuals account for each individual's own true change trajectory (defined by r_{0i} and r_{1i}).

In Model H, the estimated initial score on *Identity* for students in non-SL sections who indicate a low intent to complete a major in engineering is statistically significant at $\beta_{00} = 2.67$, $p<0.001$. The estimated differential in initial predicted *Identity* scores between non-SL and SL participants, controlling for intent, is not significant $\beta_{02} = -0.35$, $p= 0.50$, and the differential in initial score between high intent and low intent students, controlling for service, is significant $\beta_{05} = 0.27$, $p<0.01$. The estimated rate of change in *Identity* scores for non-SL participants who indicate low intent is non-significant ($\beta_{10} = 0.15$, $p= 0.56$), suggesting that a change in identity over time is minimal for the data. Service ($\beta_{12}=0.68$, $p<0.10$) impacts the rate of change for students who indicate a high intent, and *Intent* ($\beta_{15}=-0.03$) does not greatly affect the rate of change for all participants. Lastly, a minimal change in within-person variance exists, between-person variance, and covariance from the unconditional growth model.

In other words, this model predicts that both participants in SL and non–SL sections who begin the semester with a higher intent to complete a major in engineering also begin with a higher intercept for *Identity* (0.35 points greater) than their peers who begin with low intent.

Participants in non-SL sections with low intent will not differ in their *Identity* scores over time (-0.03 points per time) while students in SL sections with low intent increase their *Identity* scores at a greater rate than all of their peers (0.68 points per time). Difference in intercept for intent to complete a major in engineering and rate of change for SL sections are considered statistically significant. These relationships are visually represented in Figure 4.2, again using a prototypical score of 2 to represent low intent and a score of 4 to represent high intent as determined by the empirical middle of the students' scores.

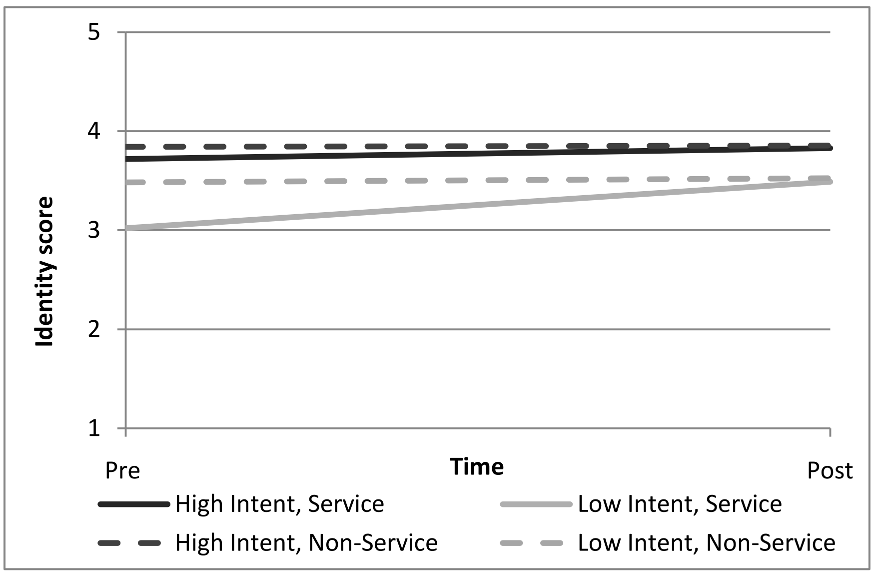

Figure 2. Prototypical change trajectories recovered from the HLM analyses for *Identity* scores in 272 subjects by intent, service, and their interaction. Time is reported in test administration.

In order to confirm the patterns in Figure 4.2, we took a closer look at the individuals in the FYEP cohort of students by both intent and service. The individual graphs of changing identity over time indicate significant individual variation within groups of students who initially ranked their *Intents* differently, also divided by SL and non-SL courses. A residual file was created and analyzed in SPSS. Empirical Bayes correlations between EB estimates of intercept and time were highest for the students that initially scored their *Intents* near 3 or 5 and were in non-SL sections of the course (*r*=-0.37 and -0.40), suggesting that the biggest changes in identities were for this group. An examination of the sum of the fitted and residual (EC) correlation for the cohort was negative, offering a pattern of highest growth that is greatest for those students with the lowest scores. Again, to mitigate the impact of the ceiling effect, we compared a restricted range of students who had predicted initial pre-survey *Identity* scores between 3 and 4. The correlations for the smaller group of students were even lower, indicating that the students in the "middle" (*n*=150) grew differently than the entire group (*N*=272). In comparing the means of the restricted set, we found little difference in mean for intercept and growth for students in SL sections, while we found more variation in slopes of students in non-SL sections. The students in non-SL are changing over time differently from each other. The correlations of the EC scores for the restricted group show a switch in directions from a negative to positive correlation between students in SL (*r*=-0.13) and non-SL sections (*r*=0.01) for students who had initial *Intent* scores close to 3, suggesting that, for this subset of students, students in SL sections with low scores increased over time and similar students in non-SL sections maintained or slightly decreased in identity over time, which is consistent with Model H.

Pseudo R^2 Statistics and Goodness-of-Fit

Overall, very little change was found in within-person variance, between-person variance, and covariance from the unconditional growth model. In examining pseudo-R^2 statistics and goodness-of-fit for the identity analyses, all study models maintain a consistent R^2_ε that explains the degree to which adding a growth variable alters the model. This confirms that the addition of any predictor variables to the level 2 model helps to explain the model without altering the original growth model. In examining R^2_o statistics, no study models really provide much further explanation (R^2_o <0.03) in defining the initial status of participants in the study, except Models F and H have an R^2_o of 0.13, indicating that *Intent* helps explain approximately 13% of the variation in initial status. Also, all models have relatively low R^2_1 (R^2_1<0.06), indicating that little further explanation of the variation in rates of change in the model exists. In other words, no models provide any more explanation in defining the rate of change in the model beyond the conditional growth model. Lastly, Model F displays the second lowest deviance and lowest AIC (a penalty on the relative goodness-of-fit that accounts for the number of parameters in the model), indicating that it may be the best overall fit of our data and the addition of intent to complete a major in engineering did somewhat improve our model of *Identity*.

A Brief Look at Retention

When study participants were categorized by retention into their second year of engineering, retained students (*n*= 242, 89%) maintained moderately high levels of identity over the course of the fall semester. Students who were not retained into their second year of engineering (*n*=30, 11%) showed a slight decrease in their *Identity* score over the course of the semester, suggesting that the students who left engineering were already moving away from identity with the profession as early as their first semester. When students were further examined by both retention and participation in a SL-based section of the course, those who were not retained in non-SL sections decreased in *Identity* scores even more that the students in SL sections who were not retained.

Limitations of the Study

The findings of these analyses must be placed within the limitations of this study. First of all, the cohort of participants comes from one semester of FYEP at the University of Colorado Boulder, which limits the generalizability of the findings. Also, not all students who entered as engineering majors in fall 2010 took the FYEP course (N=292, 41% of 2010 incoming freshmen class). While several majors require the FYEP course, not all majors do at this time. Courses and experiences outside the FYEP course also impact student perceptions and attitudes. However, most first semester students take very similar courses regardless of major (calculus, calculus-based physics or chemistry for engineers, a one-credit introduction to engineering course, and a social-science or humanities elective). It would be useful to extend this study to all entering first-year students across semesters to see if the trends continue.

Another limitation is instructor to instructor variation. To try and lessen the impact of variability in course instruction, various assignments and rubrics are offered to all instructors during a weekly FYEP meeting, intending to provide all instructors with the same resources and background research on student learning. Of course, even with such resources, consistency is impossible to enforce in actual classroom implementation. In an effort to understand instructor and section variability, the Faculty Course Questionnaire (FCQ) ratings (the college's required student survey completed at semester end for each course offering) were compared. These surveys ask students to rate different aspects of the course and instructor on a scale of 6. The students in the five PBSL sections had less variability in their ratings by section, and rated the course overall (average = 5.02, range: 4.5-5.3) and instructor overall (average = 5.12, range: 4.6-5.6) with relatively high scores. All but one of these instructors had taught FYEP before with only one presenting a new SL project. The FCQ scores of the new instructor were the lowest for the group, while the FCQ scores of the instructor who switched project topics remained high between SL and non-SL topics. For the five non-SL PBL sections, a high variability in course ratings were reported; the students in these sections recorded wider ratings ranges for the course overall (average =4.47, range: 2.0-5.5) and instructor overall (average =4.88, range: 3.0-5.8).

Most of the instructors in the non-SL sections had taught FYEP before with the project topics and FCQ scores remaining consistent with previous years. The two, new, non-SL instructors had high scores (at least 5.4 for each factor). It is likely that these ratings are mostly impacted by satisfaction with course project, perceived instructor availability, and grades. As we continue to gather data on FYEP participants, the increased data pool will provide more comparable sets of sections to analyze. More and more, the FYEP instructors are using either actual or theoretical project-based service-learning as a context for their design topics, also changing the way SL is taught in the classroom.

As for the survey items used in this study, it is important to note that the variable of "intent to complete a major in engineering" was measured using one item, eliminating the ability to confirm the students' perception through multiple variations of the question.. This item was asked both pre-and post-semester and measured student intentions with respect to completing any (current or different) major in engineering. It remains important to understand why students leave engineering, and we recommend that future students are queried about their change in attitudes after their first semester of an engineering undergraduate degree.

Discussion

Based on the current literature around design courses and service-learning in engineering, we expected to find that engagement in PBSL design during the first semester of engineering undergraduate study positively predicts students' identity with the profession of engineering over time. For this cohort of students, little change in identity was measured during the semester-long FYEP course. We discovered that the calculated trajectories of first-year engineering students' identity during the first semester of engineering undergraduate study do not differ greatly by gender, reinforcing the findings of the Academic Pathways Study (APS) that suggest engineering identity does not vary considerably by gender (Atman et al., 2010). We also did not find a large predicted change in identity trajectory by just participation in a service-learning section (see Table 4.4). Overall, the greatest impact on the students' changing identity over time was intent to complete a major in engineering.

We used prototypical values of 2, 3, and 4 to represent low, medium, and high self-reported intent to complete any major in engineering, based on the empirical middle values of students' scores. This "middle" group also represents the students who come into engineering without an initially high identity, a faction we really want to reach. Students with an initially high intent to complete a major in engineering are predicted to maintain a high identity with the profession over the course of the semester. Our models predict that students with lower initial scores on intent all increase their identity with the profession over time. Lastly, students with the "lowest" intent increase their identity at a relatively greater rate than their peers. When further examined by service, students in SL sections start with slightly lower *Identity* scores and have greater gains over the semester than their peers in non-SL sections. While none of the gain values are large from a practical standpoint, it is possible that SL may help increase identity over time for students who had initially lower intent to complete a major in engineering, which are the group of students targeted with this study.

Interest in whether real-world problems or service learning context increase students' identity with the profession of engineering and their intent to find careers in the field is gaining momentum. (Bielefeldt et al., 2009; Harding et al., 2010; B. D. Jones et al., 2010). As we continue to survey our FYEP students with respect to their identity with engineering, we will expand the data set to include attitudes and intent across multiple cohorts and years. The expanded data set will be useful to substantiate the patterns found in this initial study cohort of

FYEP course students. Following the body of research that indicates participation in SL courses leads to significant and enduring increases in identity for undergraduate students in liberal arts and education majors, it would be interesting to follow these engineering students after another two years in undergraduate studies and see if the impacts persist (Batchelder & Root, 1994; S. R. Jones & Abes, 2004).

Our brief look at retention indicates that students who left engineering were already moving away from identity with the profession as early as their first semester; with those not retained in non-SL sections decreasing in *Identity* score even more that the students in SL sections who were not retained. We also want to take a closer look at the retention of students in this cohort, examining the model of how identity over time and changing intent predicts students' retention into their second year of engineering (with retention as the outcome variable).

Throughout the literature, the belief that engineers contribute to improving society resonates with a diverse group of students, which supports project-based service-learning as an instructional method that can impact the dynamic attitudes of identity in first-year engineering undergraduate students and potentially increase the retention of capable and interested students. We agree that the opportunity to engage in engineering for "social good" has the potential to impact many facets of students' growth throughout their undergraduate careers. Based on the results of this study, undergraduate institutions seeking to increase students' identification with the profession of engineering should consider both surveying students' intent to complete engineering majors as well as engaging students in project-based service-learning experiences as early as first semester of the freshman year.

CHAPTER V

IMPACT OF PROJECT BASED SERVICE-LEARNING ON HIGH SCHOOL STUDENTS' DEVELOPING IDENTITY WITH ENGINEERING

Introduction

Today's students exhibit a decreased motivation to choose futures in science, technology, engineering, and math (STEM); however, our nation's need for science and engineering innovation has never been more critical. National priority for a stronger STEM education focus at the K-12 level is at an all-time high, with significant federal funds set aside for state educational agencies to finance efforts to integrate engineering education into K-12 instruction and curricula (111th Congress, 2010). Unfortunately, research reveals that K-12 students are not considering math and science as professionally relevant —closing off future career pathways as early as third grade (S. L. Turner & Lapan, 2005). In fact, the proportion of U.S. high school students who choose to obtain science and engineering degrees in college continues to stay lower than in many other countries (National Research Council, 2009). This lack of interest in STEM disciplines is particularly apparent among disadvantaged groups that have been underrepresented in those fields (National Research Council, 2007, 2010). The National Academies' *Rising Above the Gathering Storm, Revisited* publication (2010), reminds us that amidst a growing population of minority students we are still not encouraging or attaining a diverse population in STEM undergraduate programs (National Research Council, 2010).

The U.S. population of college-aged students of all racial/ethnic groups is projected to increase (non-Hispanic Caucasians will comprise less than 50% of the college-aged population by 2025), which is not good news for engineering colleges that historically struggle to attract these diverse populations into their ranks (American Society for Engineering Education, 2009; Sullivan, 2007; Tienda, 2009; U.S. Census Bureau, 2008). African Americans and Hispanics comprised ~32% of college-age populations and 23% of college student populations in the U.S. in 2007, and only collectively accounted for 11% of engineering bachelor's degrees awarded in 2009 (American Society for Engineering Education, 2009; Gibbons, 2010). The participation of women in the engineering pipeline has been slowly decreasing from its peak in 2002 at around 21%, now accounting for closer to 18.1% of engineering bachelor's degrees awarded in 2010, up slightly from 17.8% in 2009 (American Society for Engineering Education, 2009; Engineering Trends, 2008; Gibbons, 2010; National Science Board, 2010a). Since only 4.5% of U.S. BS graduates earn engineering degrees, this means less than 2% of the nation's engineering BS degrees are awarded to minorities and women annually.

Research suggests that recruitment into undergraduate engineering majors may be related to early exposure to engineering and knowledge of engineering disciplines, leading to greater professional identity with the discipline, increased learning of higher level technical and professional skills, and hopefully persistence in engineering (Beam et al., 2009; Fantz et al., 2011; Ohland et al., 2008; Pierrakos et al., 2009; Schunn, 2009). Fantz (2011) compared first year engineering undergraduate students who had pre-collegiate experiences and found that a higher exposure to engineering content during K-12 led to higher self-efficacy in undergraduate first year engineering, especially semester-long classes at the high school or middle school levels (which has also been suggested to lead to increased performance and persistence) (Fantz et al., 2011). Although a small number of grade K-12 students may go on to engineering careers, the exposure to engineering at the K-12 level can also lead to more technologically-literate citizens and possibly increased diversity of engineers (Schunn, 2009; Sullivan & Zarske, 2005).

In their 2009 publication entitled *Engineering in K-12* Education: Understanding *the Status and Improving the Prospects*, the National Academy of Engineering's Committee on K-12 Engineering Education noted that the real-world problem solving nature of engineering led to an improved learning of the fundamental science and math principles that students explore early in their education and an increased interest in these topics the K-12 level (Katehi et al., 2009). They recommend that design can be enhanced for K-12 students by placement in a more personal or local-community real-world context. This recommendation provides support for the use of project-based service-learning (PBSL) as a mechanism for teaching core engineering concepts in the K-12 classroom. Such client-based projects have already shown positive impacts on undergraduate students' motivation, critical thinking skills, professional and technical skills, identity and self-efficacy, interpersonal skills, attitudes towards community service, and recruitment/retention (Astin et al., 2000; Bielefeldt et al., 2009; Coyle et al., 2003; Duffy et al., 2009; Fisher et al., 2005; Freeman, 2011; Harding et al., 2010; Lemons et al., 2011; Williams et al., 2009; Zarske et al., 2011). In short, by experiencing the engineering design process within a societal context early on in their education, students begin to see how engineering advancements and innovations shape their everyday lives, and they begin to develop an identity that opens the door to a technological or STEM future.

This paper examines the impact of PBSL in existing high school engineering design courses. Specifically, we observe the change in identity attitudes for a cohort of 10th and 11th grade high school engineering students engaged in an engineering project-based design course and whether a service-learning context, gender, and ethnicity impact these change trajectories.

Related Literature on K-12 Engineering, Service-Learning, and Identity

Many K-12 engineering education initiatives implemented by U.S. universities and colleges have been well documented, providing us with descriptions of program logistics, partnerships, methods and curricula; as well as the impact on involved students, teachers and undergraduate and graduate students. The increasing number of members in the American Society of Engineering Education's (ASEE) K-12 and Pre-College Engineering Division, now ranked as the 12th largest division of 50, is a testament to the growing enthusiasm for formalized engineering partnerships in the K-12 arena. The sheer numbers of conference papers on K-12 programs and partnerships that have been presented during the past few ASEE Annual Conferences further demonstrate the importance of collaboration and determination of best practices in K-12 engineering curricula, content delivery approaches, and teacher professional development. However, engineering is still far from being a standard in every K-12 school curriculum. Given the growing trends in K-12 engineering education and the demonstrated benefits from some K-12 engineering programs, it is imperative to increase quality research around the learning of engineering at the K-12 level to better determine the impact for evolving STEM instruction in K-12 schools and the best practices for implementation.

A review of the literature and the afore mentioned recommendations by the National Academy of Engineering's Committee on K-12 Engineering advocate for project-based engineering design experiences (PBL) as an instructional method to increase K-12 student knowledge and attitudes towards engineering. In effect, PBL uses real-world problems and carefully designed tasks that reflect the environment in which children now live and learn, encouraging collaboration with other students, and culminating in a final product, such as a design, model, device, or computer simulation (Markham et al., 2003; Prince, 2006). Evidence at the K-12 level shows that a project-based instructional method provides a motivating environment for the teaching of basic skills, increases student understanding of more complex problems, and increases student exhibition of higher professional skills and creativity, than students that are taught traditionally (Brophy et al., 2008; Markham et al., 2003). Analysis of hands-on, project-based engineering design activities in the K-12 setting also demonstrates an increase in students' STEM content knowledge and interest in engineering (Zarske et al., 2007).

Research at the undergraduate level suggests that incorporating a more local-community, service-learning (SL) context into existing design experiences can increase learning of technical, professional, and interpersonal skills, and provide students' with a deeper understanding of the social context of their work (Astin et al., 2000; Bielefeldt et al., 2009; Jacoby & Associates, 1996; S. R. Jones & Abes, 2004; Lemons et al., 2011; Lima & Oakes, 2006; Seider et al., 2011). It seems as if SL appeals to a wide audience because of its roots in helping the greater community, or social good. When asking undergraduate students what motivates them to study engineering, social good consistently appears ranked among top motivational factors by both males and females (Atman et al., 2010; Duffy et al., 2009; Pierrakos et al., 2009; Sheppard et al., 2010). This motivation does not seem to alter much over the course of an undergraduate degree program, suggesting that some of these factors may occur significantly pre-college or during the first years of undergraduate degree studies (Sheppard et al., 2010).

SL is often found in combination with project-based learning to form project-based service-learning (PBSL). There are distinct components of PBSL that allow students to learn at a more meaningful and complex level, including: service to an underserved area or people; diverse academic content; partnerships in and around the community; mutual learning of students and community participants; engaging multifaceted problems in complex settings that promote problem solving and critical thinking, and reflection (Lemons et al., 2011; Lima & Oakes, 2006). Programs engaged in PBSL efforts at the K-12 level indicate that subject matter that engages students in cooperative approaches, focuses on global impacts, and is placed in a local-community context may be a key factor in the recruitment of minority and female students into engineering offerings (Matyas & Malcolm, 1991; Mihelcic et al., 2008; Noddings, 1992; J. Oakes et al., 1992; Seider et al., 2011; Sullivan & Zarske, 2005; M. Thompson et al., 2008; Zimmerman & Vanegas, 2007). However, there is very little previous work available in the K-12 literature that determines any specific psychological and educational benefits from engaging in service-learning as compared to non-SL project experiences.

PBSL may also influence the formation of identity with the engineering profession for students (Bielefeldt et al., 2009; Stevens et al., 2008). Self-reported knowledge plays a large role in professional identity, suggesting that students who know more about the discipline are more likely to relate themselves to the discipline (K. Adams et al., 2006). As students interact with a discipline-specific learning community, such as engineering students, they begin to form discipline-based identities that result in a cycle of individual identity and communities reinforcing each other (Pierrakos et al., 2009; Plett et al., 2011). The growing body of research indicates that participation in SL courses lead to significant and lasting increases in identity (Batchelder & Root, 1994; S. R. Jones & Abes, 2004). Further research on student identification with engineering, how identity motivates students to pursue engineering degrees, and how different views of the nature of engineering manifest in developing engineering identity, is repeatedly recommended in the literature (Atman et al., 2010; Matusovich et al., 2011; O’Connor et al., 2006).

Several researchers have also concluded that an overall deficiency of engineering-related curricula in K-12 essentially leads to a lack of understanding how students can engage in engineering when compared to other STEM fields, limiting the numbers of qualified students that migrate into engineering degrees (Beam et al., 2009; Ohland et al., 2008; Stevens et al., 2008). This problem is larger than initially choosing an engineering pathway out of high school; while 60% of graduates in science started in other majors, over 90% of graduates in engineering started in engineering (Ohland et al., 2008). The Center for the Advancement of Engineering Education (CAEE) reports that as few as 20% of students of first-year engineering students had any significant exposure to engineering before coming to an engineering college (Atman et al., 2010). These students had little knowledge of what engineers do; something which is essential to forming an identity as an engineer. The case may be worse for females, who are more likely to mention not having any exposure to engineering prior to college (Pierrakos et al., 2010). Incorporating PBSL design into K-12 classrooms to increase pre-college exposure to engineering may also capture the interest of a diverse population of students, including women and minorities, into engineering undergraduate careers and future STEM workforce.

Research Questions

This study examines high school students' perceptions of identity with engineering. Specifically, we explore the following research questions in this paper:

1. Do 10^{th} and 11^{th} grade high school students engaged in project-based design change their identity with a group of engineering students over time?
2. Is there a relationship between students' identity trajectory and a service-learning context, gender, and/or ethnicity?

Methods

Setting

An engineering design elective course, *Creative Engineering Design*, at Skyline High School in Longmont, Colorado, is the setting for implementing this project's research and has been described by the authors in previous articles (Zarske, Ringer, Yowell, Sullivan, & Quiñones, 2012; Zarske et al., 2012). This high school has created a widely-promoted high school STEM certificate program to bring highly-interactive, hands-on STEM projects into the classroom to capture the attention of students at risk of early school dropout. Resolute that the "E" in STEM should not be a *silent* vowel, the program has an engineering focus, with three full years of STEM engineering courses required to earn a Skyline STEM Academy certificate. One of the goals of the STEM Academy is to mirror the demographics of the school population, ensuring that the program is serving their whole population—including minority youth and girls, and low-income youth from all backgrounds. The STEM Academy opened in fall 2009 with 80 freshman and 12 sophomores, and grew to 249 students in fall 2011, comprised of 35% female, 35% minority (largest minority population is Hispanic), and 23% free- and reduced-lunch students across grades 9-12. The first four-year STEM Academy cohort to graduate will do so in 2013.

Students begin the STEM engineering sequence in 9th grade with exploring the engineering design process and the importance of teamwork in engineering. During the more advanced *Creative Engineering Design* class, they can choose to focus on topics from Assistive Technology, Biotechnology, Sustainable Design, and Structural Design. The *Creative Engineering Design* class engages student teams in a semester-long, project-based engineering exploration that follows an engineering design process, beginning with specification of design objectives, research, brainstorming, idea refinement, and culminating in development and mathematical analysis of a prototype for the chosen solution. Reflection components include a mid-semester focus group discussion, an end-of-semester journal assignment, and open-ended post-survey questions. Thus far, the Biotechnology sections for Creative Engineering have focused on the design of a product for a local community client.

Participants

The analysis in this report contains survey data information from 102 10^{th} and 11^{th} grade students enrolled in *Creative Engineering Design* during the 2010-2011 academic year. For this inaugural year, three topics of *Creative Engineering Design* were offered: Assistive Technology (Robotics), Biotechnology (service-learning for a local community client), and Structural Design (Cranes). While the majority of the students were in 10^{th} grade (n=80, 78%), 22 upper-class students (22%) were also enrolled in the course given that it was not offered the year before. Participants included 31 females (30%) and 71 males (70%). Also for this analysis, majority students included both female and male Caucasian and Asian students (n=61, 60%), while underrepresented minority (URM) students included female and male Hispanic, Black, and multicultural students (n=41, 31%, 4%, and 5% respectively). All students reported engaging in informal service opportunities (such as church activities, helping at the local community or animal shelter, and tutoring younger students) previous to the course, while 24% of students reported actively participating in service 2-4 times per year.

Over the year, seven sections of the course were offered, with three of the sections engaged in project–based service-learning (PBSL) projects and the other four sections engaged in non-service PBL projects. Students were aware of the general section topics prior to registration, and enrolled in different sections based on interest and timing of other required courses. In 2010-2011, the PBSL client was a young girl from the elementary school next door who has arthrogryposis, a condition that limits the movement of her joints at the wrists, elbows, and knees. The high school students designed original products to help their client access a drinking water fountain more independently. They met with their client several times throughout the semester, and she chose her favorite product at the end of the semester, bringing together local community and real-world contexts for engineering design. The non-service PBL projects included robotic rovers and crane-structure designs.

Most students were enrolled in two different sections of the course over the year, to fulfill STEM Academy requirements. For example, several students completed PBSL projects during the fall and non-service PBL projects during the spring semester. This resulted in a set of participants with varying levels of engagement in PBSL, which will be discussed further under the variables section of this paper. The two *Creative Engineering Design* teachers cooperatively developed and implemented the same project schedule, checkpoints, and grading rubrics for each section. During the year, one teacher taught the three PBSL sections of the course, while the other teacher taught the four non-service PBL sections.

Assessment Instrument Design

Students were given an online engineering attitude survey during class in the first and final weeks of each semester, with choices on a five-point Likert-type scale for each survey question ranging from “not at all” to “definitely.” The intent was to measure any change in student attitudes towards engineering as a result of exposure to the *Creative Engineering Design* experience. Since some students were enrolled in *Creative Engineering* during both the spring and fall semesters, each student participant completed between 2 and 4 surveys over the 2010-2011 year.

Students typically completed the survey instrument within ~20 minutes. The survey instruments were in part modified from existing instruments already in use by the University of Colorado Boulder to evaluate their *First-Year Engineering Projects* course (Zarske et al., 2011). Survey questions that related to the goals of this study were adopted from previously developed surveys for primarily undergraduate engineering and integrated into the existing high school survey, including:

- The Community Service Attitudes Scale, which assesses the degree of participants' attitudes regarding community service (15 items) (Shiarella et al., 2000).
- The Engineering Identity Survey developed by Chachra et al., which assesses the degree of participants' group identification with engineers (11 items) (Chachra et al., 2008).
- The Academic Pathways Study (APS) and the Assessing Women and Men in Engineering Project (AWE; version for middle and high school level), designed to examine how student attitudes, skills, and efficacy change over time (27 items) (Assessing Women and Men in Engineering, 2006; Chen et al., 2008).

These items comprised the dependent variables in this study (n=53). In addition, demographic data such as gender, ethnicity, and year/grade, were collected with missing values retrieved from the high school student database. Surveys for all participating students are conducted under the University of Colorado Boulder's Institutional Review Board (IRB) approval, reviewed annually by external and internal evaluators. Student responses were coded to protect participant identity.

The quantitative survey items, coupled with qualitative answers to open-ended survey questions, cumulatively query students' changing attitudes over time. Theory would suggest that our high school survey measures five separate constructs: student perceptions of their awareness of engineering, student interest in engineering, student self-efficacy in engineering, identity with the engineering profession, and attitudes towards community service.

Our instrument was examined to gather evidence of validity by analyzing how well the items measure the constructs that we intended. High inter-item reliabilities suggested that the survey items could also be reduced to a smaller number of associated factors through factor analysis. A Principal Components Analysis (PCA) was performed on the sample to analyze the theoretical constructs represented by the sets of response items in the survey. The number of factors was determined by examining the total variance explained as well as a Cattell's Scree test. In this analysis, the Scree plot suggested that there was a five- or six-component solution. PCA was re-run using both five and six dimensionalities, and the results were compared. Very little explanatory power was added by including a sixth dimension, so a five-factor solution was chosen. PCA also suggested that attitudes towards community service may correlate significantly with students' awareness of needs that can be met by engineering, though not very strongly. The average of the items that loaded on a given factor is used as dependent variables in the remainder of this analysis.

Variables in Analysis

Many different variables are necessary to examine the longitudinal change in perceptions and attitudes of high school students in engineering. The independent variables for this analysis, to potentially explain the variation in attitudes and perceptions between groups of students, were selected on the basis of research on service-learning and hands-on projects. While many combinations of independent and dependent variables could be examined from this data set, this paper will focus on the student perception of identity with the STEM Academy and engineering

(12 items after factor loading). The remaining factors will be discussed in future papers. Example survey items for the factor of identity are presented in Table 5.1.

Table 5.1. Survey Items for *Identity* in the Skyline High School survey

Factor, Number of Questions, and example constituent items
Identity (12 items)
How much do you agree with the following statements
In general, being a STEM student is an important part of my self-image.
I identify with the students in my engineering classes.
I feel good about engineers.
I am glad that I belong to a group of engineering students.
I see myself as an important part of engineering students at school.
I feel strong ties to engineering students.
Being a STEM student is an important reflection of who I am.

Other variables collected for this analysis include the demographic variables of gender (31 females and 71 males) and ethnicity (61 majority-identifying students and 41 students identifying with underrepresented minorities or URM). A variable of time is used in this analysis to represent each administration of the survey throughout the year.

As mentioned earlier, there were many ways that students could engage in PBSL for the Creative Engineering Course over the year. Basically, some students only took one SL or non-SL section of the course in the fall or spring semester, some students took the SL section in the fall and the non-SL section in the spring, some students took a non-SL section in the fall and an SL section in the spring, and still other students took two consecutive non-SL sections over the year. To make things more complicated, a small handful of students took an SL and a non-SL section during the same semester. In order to model and take a numerical look at the impact of the various levels of SL on students' changing identity with engineering, multiple "dummy" variables were created to take the place of the now multi-leveled nominal SL variable (See Table 5.2). The first dummy variable, Service_1^{st}, represents students whose first (or only) section of enrollment in *Creative Engineering* was an SL section whether it was in the fall or spring (n=38).

Service_2^{nd} represents students whose second section of enrollment in *Creative Engineering* was an SL section (*n*=43). And, finally, the group that both of these variables will be compared to is enrollment in two consecutive non-SL sections (*n*=21). The addition of two SL variables will help us determine if any engagement in SL (as opposed to no engagement in SL) over the course of the academic year has an impact on students' identity with engineering. A summary of the variables in this analysis can be found in Table 5.3.

Table 5.2. Revised "dummy" variables for service, used in analyses.

Variable	Section order	Number of students (Female, URM)
Service_1st	Only PBSL	27 (9, 11)
	PBSL - PBL	11 (4, 7)
Service_2nd	PBL - PBSL	43 (11, 12)
None	PBL - PBL	21 (7, 11)

Table 5.3. List of variables included in the analysis, along with descriptions of each.

Variable	**Description**
Identity	Represents outcome variable of interest; Composite measure of self-reported attitudes towards identification with engineering discipline and engineering students; Continuous variable; Average score of 12 items measured on a 1-5 Likert scale
Gender	Represents a dichotomous, independent variable of student gender; 0=Male and 1=Female
URM	Represents a dichotomous, independent variable of student ethnicity divided into underrepresented in engineering (URM) and highly represented in engineering (Majority); 0=Majority-identifying students and 1=URM-identifying students
Service_1^{st}	Represents an independent, "dummy" variable of initial/only enrollment in an SL-section of *Creative Engineering*
Service-2^{nd}	Represents an independent, "dummy" variable of second semester enrollment in an SL-section of *Creative Engineering*
Time	Represents an independent variable of time of survey administration; students enrolled in two consecutive semesters of *Creative Engineering* could have up to 4 sets of survey item responses; 0=initial administration, 1=second survey administration, and so forth

Statistical Analysis

The average of the 1-5 Likert- scale responses that loaded on the *Identity* factor is used to represent the dependent variable at each time of the survey administration. For example, a higher average of the survey item scores for *Identity* on their initial survey during the program indicates a student's greater initial overall perception of their identity with engineering and other engineering students. Next, this and other variables were matched for each individual over each administration.

First, we analyzed the data for missing values and data entry errors. There were only two students who only completed one survey over the entire year and were excluded from the data set prior to analysis. Any missing values were examined for patterns, and no student skipped more than one or two items in each administration of the survey. Missing survey data was handled during subsequent analyses with list wise deletion. Missing demographic data was retrieved from the high school student administrative records.

Initial data screening began with inspecting empirical growth plots and superimposing fitted OLS-estimated linear trajectories for the individual subjects. This plot suggests interindividual heterogeneity in change, and a general pattern emerges. For the entire population in the study, participants either increase or decrease their identity with engineering over time, with an average of no change for the population as a whole. The plots also suggested trends in *Identity* score data that indicate a "ceiling effect," where some students start with the highest score on self-perceptions of identity and stayed there throughout the year. We then looked at three sub-groups of students — high-starters, middle-starters, and low starters — to see if there were mean pattern differences between the middle and high or low outliers. We noticed that the middle and low-scoring students moved more than their peers in the high-scoring group, confirming the potential ceiling effect. To mitigate impact of the ceiling effect, and to focus in on the students who we really want to reach, we chose to compare a "restricted range" of students who had an initial pre-survey *Identity* score below 4.5. This range essentially removed the highest scoring students (20%, *n*=21), thus making the analysis more sensitive to scaling issues. For these analyses, IBM SPSS statistical software package (version 20) was used.

Developing a Multilevel Model for Change to the Restricted Set of Data

Next, we developed a model to predict *Identity* from viable predictors of change. Our data includes both variables that describe individuals and variables that describe groupings of individuals, common to education research. We wanted to develop a model that can estimate both course- and individual-level effects on our outcomes and relationships of interest. Traditional regression does not effectively model nested systems, since it assumes that all effects occur at either the individual or group level. The type of complex systems model for the *Creative Engineering* data can be better represented using a hierarchical linear modeling (HLM). HLM allows the researcher to represent the relationships between variables on one level (such as individual-level) while also considering the influence on relationships at another level (such as course-level) (Raudenbush & Bryk, 2002). Education researchers often use HLM in the development of models where the independent variables are on multiple levels (individual, course, or school), and the dependent variable is at the lowest level of analysis (Borchers & Sung Hee Park, 2011).

The first step in developing a multi-level model for change includes suggesting a level-1 model that can describe the intercept and rate of change for an individual within the *Creative Engineering* course. In other words, for this population, the dependent variable of *Identity* was considered a linear function of individual *i*'s TIME on occasion *j*. Since our data set is longitudinal over an entire year, and we have four distinct time occasions to consider, time was centered on the first occasion in which the data was collected (TIME 0) in order to facilitate interpretation of the intercept. Our level-1 model thus includes sequential TIME_1, TIME_2, and TIME_3 to represent the end of the first semester, beginning of second semester, and end of second semester, respectively.

The level-2 model represents the hypothesized effects on how the level-1 individual growth parameters are related to between-subject factors, such as service, gender, and URM. To develop level 2 models, the level-1 individual growth parameters of true initial status and true rates of change were used as outcomes, creating two level-2 sub models for interindividual differences in change. These level 2 models speculate the existence of an average trajectory of the population for each between-subject factor for each survey occasion. The level-2 residuals account for each individual's own true change trajectory. Regression analyses were conducted to examine the relationship between the dependent variable of *Identity*, participation in SL-based sections of the course, gender, and URM.

To find the best values for parameter estimates, we used a Full Maximum Likelihood (FML) estimation method. FML estimation provides estimates for values of unknown population parameters that maximize the possibility of observing the specific sample of data (Singer & Willett, 2003). This method estimates contain all of the fixed effects as well as the variance components from the model, and therefore describe the fit of the entire model. Our FML estimate of the data was completed using Hierarchical Linear and Nonlinear Modeling (HLM) software, a modeling software distributed by Scientific Software International, Inc. ("Hierarchical Linear and Nonlinear Modeling (HLM)," 2011).

These analyses were somewhat exploratory in nature. We investigated several interrelationships between variables, and tested several combinations that did not appear into our final paper because they did not add to the overall strength of the models. In other words, some models did not offer significant regression coefficients or add significant changes in pseudo-R^2 statistics and goodness-of-fit for these analyses.

Results

Overall Course

First, to make the analysis more sensitive to scaling issues and remove any ceiling effect, we removed 21 students with a high initial *Identity* score (>4.5). This group included 15 (71%) males, 6 (29%) females, and 7 (33%) URM. Thus the group with very high initial identity was over-represented in males and non-URM students compared to the overall demographics of the overall students in the course. The average starting *Identity* score among the high sub-group was 4.73 and the average final score was 4.83 (see Table 4).

The survey results from matched surveys of the "restricted" set of 81 students enrolled in 10 sections of *Creative Engineering* during the 2010-2011 academic year included both middle ($3.3 \leq$ score ≤ 4.5) and low scoring students (score < 3.3) and are shown in Table 5.4. The pre- to post-mean scores of the overall students in Table 5.4 demonstrate a significant increase in *Identity* scores for the overall students in *Creative Engineering*. There is a larger increase in *Identity* scores over time for males than females, and a larger increase in *Identity* scores over time for URM than majority students. Lastly, those students who took a SL-section of Creative Engineering as their first/only exposure showed the greatest increases in *Identity* score over the year, with smaller changes in scores for those students who took an SL-section second or not at all. There is a fairly high standard deviation for males and majority students on their final two survey administrations, indicating that there is a large variability within this specific set of individual responses. A paired-samples t-test was used to analyze the differences in mean scores from the beginning to the end of the academic year. The resulting paired sample correlations where strong for the URM students (r=0.97), students who had SL as the first (or only) section (r=0.78), and students who had no SL sections (r=0.97), indicating that for those sub-groups, students who scored higher on the pre-survey also scored higher on the post-survey.

Table 5.4. Descriptive statistics for *Identity* score in restricted set of high school students.

	N	Min	Max	Time 0 Mean (SD)	Time 1 Mean (SD)	Time 2 Mean (SD)	Time 3 Mean (SD)	Mean Difference Within Groups from Time 0 to Time 4	Mean Difference Between Groups at Time 0
High sub-group (Initial Identity>4.5)	21			4.73 (0.12)	4.64 (0.36)	4.79 (0.21)	4.83 (0.21)	0.10	
Mid sub-group (3.4<Initial Identity<4.5)	58			4.06 (0.33)	4.20 (0.51)	4.14 (0.57)	4.19 (0.66)	0.13	1.71
Low sub-group (Initial Identity<3.4)	23			3.02 (0.32)	3.62 (0.68)	3.40 (0.85)	3.86 (0.93)	0.84*	
Resticted Group (non-ceiling)	**81**	**2.25**	**4.5**	**3.76 (0.57)**	**4.03 (0.62)**	**3.97 (0.70)**	**4.13 (0.72)**	**0.37***	
Female	25			3.84 (0.54)	3.98 (0.48)	3.91 (0.51)	3.98 (0.43)	0.14	0.11
Male	56			3.73 (0.59)	4.06 (0.67)	4.00 (0.77)	4.19 (0.82)	0.46*	
URM	34			3.83 (0.59)	4.01 (0.64)	4.24 (0.52)	4.36 (0.52)	0.53	0.12
Majority	47			3.71 (0.56)	4.05 (0.61)	3.80 (0.76)	3.98 (0.80)	0.27	
Service_1st	26			3.78 (0.52)	4.29 (0.58)	4.39 (0.42)	4.60 (0.42)	0.82	
Service_2nd	26			3.77 (0.60)	3.94 (0.60)	3.86 (0.73)	3.99 (0.77)	0.22	0.05
No Service	11			3.73 (0.61)	3.88 (0.63)	4.14 (0.64)	4.26 (0.61)	0.53	

Notes: Cell entries contain mean scores and standard deviations for the overall, high, middle, and low scoring groups as well as by gender, ethnicity, and service-learning for the restricted set of students enrolled in *Creative Engineering Design*.
*Significant at the p<0.05 level, paired t-test

Unconditional Model Analysis

First, an unconditional means model (Model A) was fit to the data that quantified the *Identity* outcome variation across participants without regard to time (see Table 5.5). This model helps determine if there is enough variation in intercept to deserve further investigation. The estimated average elevation of the true individual change trajectories (represented by β_{0x}) for identity at the beginning of this analysis differed significantly from 0 ($\beta_{00} = 3.93$; $p<0.001$), confirming that the initial score across participants is non-zero. From the unconditional means Model A, we conclude that the score varies over the duration of the study and that the individuals differ from each other.

Table 5.5. Estimates of the fixed-effects of intercept and slope (β) and variance components (σ) from various models of inter-individual differences in *Identity* score (IDY) in 81 participants over the course of the study, with standard deviations in parentheses.

			Model A Unconditional Means	**Model B** Unconditional Growth	**Model C** Growth by Service	**Model D** Growth by Gender	**Model E** Growth by URM	**Model F** Growth by Service & Gender	**Model G** Growth by Service & URM
Initial	Intercept		3.93***	3.76***	3.73***	3.73***	3.71***	3.71***	3.79***
Status,					0.14	0.08	0.08	0.17	0.19
π_{0i}		β_{00}	0.06	0.06					
	Service 1st				0.05			0.07	0.06
		β_{02}			0.17			0.21	0.25
	Service 2nd				0.04			0.00	-0.17
		β_{03}			0.17			0.21	0.22
	Gender					0.11		0.05	
		β_{04}				0.13		0.28	
	URM						0.12		-0.11
		β_{05}					0.13		0.25
	Service 1st							-0.03	
	* Gender	β_{06}						0.36	
	Service 2nd							0.17	
	* Gender	β_{07}						0.34	
	Service 1st								-0.04
	* URM	β_{08}							0.33
	Service 2nd								0.61~
	* URM	β_{09}							0.32
Rate of	Intercept			0.27***	0.15	0.33***	0.33***	0.17	0.33
change,		β_{10}		0.07	0.11	0.09	0.08	0.11	0.21
Time 1,	Service 1st				0.35~			0.38~	0.14
π_{1i}		β_{12}			0.18			0.22	0.27
	Service 2nd				0.01			0.09	-0.07
		β_{13}			0.15			0.16	0.24
	Gender	β_{14}				-0.19		-0.04	

						0.14		0.26	
	URM						-0.15		-0.31
		β_{15}					0.15		0.28
	Service 1st							-0.08	
	* Gender	β_{16}						0.36	
	Service 2nd							-0.31	
	* Gender	β_{17}						0.33	
	Service 1st								0.38
	* URM	β_{18}							0.37
	Service 2nd								-0.01
	* URM	β_{19}							0.35
Rate of	Intercept			0.20*	0.22	0.27*	0.16	0.45*	0.20
change,		β_{20}		0.08	0.16	0.11	0.11	0.19	0.25
Time 2,	Service 1st				0.27			0.11	0.28
π_{2i}		β_{22}			0.22			0.27	0.47
	Service 2nd				-0.16			-0.34	-0.11
		β_{23}			0.20			0.24	0.28
	Gender					-0.23		-0.64*	
		β_{24}				0.16		0.26	
	URM						0.15		0.14
		β_{25}					0.17		0.34
	Service 1st							0.39	
	* Gender	β_{26}						0.37	
	Service 2nd							0.48	
	* Gender	β_{27}						0.35	
	Service 1st								-0.09
	* URM	β_{28}							0.57
	Service 2nd								-0.20
	* URM	β_{29}							0.42
Rate of	Intercept			0.25*	0.36~	0.32*	0.20	0.73***	0.48
change,		β_{30}		0.11	0.22	0.14	0.15	0.17	0.33
Time 3,	Service 1st				0.23			-0.03	0.07
π_{3i}		β_{32}			0.30			0.32	0.65
	Service 2nd				-0.29			-0.64*	-0.41
		β_{33}			0.26			0.26	0.37
	Gender					-0.22		-1.00**	
		β_{34}				0.21		0.37	
	URM						0.15		-0.19
		β_{35}					0.23		0.47
	Service 1st							0.70	
	* Gender	β_{36}						0.56	
	Service 2nd							0.92*	
	* Gender	β_{37}						0.45	
	Service 1st								0.33
	* URM	β_{38}							0.80
	Service 2nd								0.15
	* URM	β_{39}							0.57
Variance components									
Level 1:	Within		0.21	0.00	0.00	0.00	0.00	0.00	0.00
	person, ε_{ij}	σ^2_{ε}	0.46						
Level 2:	In initial		0.21	0.32	0.32	0.32	0.32	0.32	0.30
	status, ζ_{0i}	σ^2_0	0.04	0.05	0.05	0.05	0.05	0.05	0.05
	In rate of			0.39	0.37	0.39	0.39	0.36	0.35
	change, ζ_{1i}	σ^2_1		0.06	0.06	0.06	0.06	0.06	0.06
	In rate of			0.47	0.43	0.45	0.47	0.42	0.44
		σ^2_2		0.09	0.08	0.08	0.09	0.08	0.08

change, ζ_{2i}								
In rate of			0.80	0.76	0.79	0.83	0.73	0.78
change, ζ_{3i}	σ^2_3		0.15	0.14	0.15	0.15	0.13	0.14
Covariance			-0.25	-0.26	-0.24	-0.28	-0.25	-0.27
	σ_{01}		0.07	0.07	0.07	0.07	0.07	0.07
Pseudo R^2 Statistics and Goodness-of-Fit								
R^2_ε			1.00	1.00	1.00	1.00	1.00	1.00
R^2_0				0.00	0.00	0.00	0.00	0.06
R^2_1				0.05	0.00	0.00	0.08	0.10
R^2_2				0.09	0.04	0.00	0.11	0.06
R^2_3				0.05	0.01	-0.04	0.09	0.03
Deviance		443.42	379.62	369.21	377.62	371.62	354.21	350.52
AIC		449.42	407.62	413.21	413.62	407.62	422.21	418.52
BIC		742.24	1097.44	1209.97	1163.80	1157.80	1313.38	1309.69

~p<0.10; * p<0.05; **p<0.01; ***p<0.00

Next, we fit an unconditional growth model (Model B), adding the predictor variables of TIME_1, TIME_2, and TIME_3 into the model and examining the elevation and linear rates of change (slope) for *Identity* across participant's entry and time the study. This model creates a baseline model for change over time and differs from the unconditional means model by examining the scatter of each person's scores around their linear change trajectory instead of their mean intercept with an assumed flat trajectory as in Model A. The estimated average elevation of the individual growth in *Identity* score at the beginning of the study differed significantly from 0 (β_{00} = 3.76; p<0.001), suggesting that the true individual change *Identity* trajectory still has a non-zero intercept. The variance in initial status confirmed significant variability for prediction at level 2 in subsequent models. The estimated average rate of change for *Identity* (represented by $\beta_{1x,}$ $\beta_{2x,}$ β_{3x}) also differed from 0 at each time, (β_{10} =0.15, β_{20} =0.22, and β_{30} =0.36) indicating that change over time was evident in the data. The level 2 variance component associated with rate of change was also statistically significant, suggesting that there are amounts of variation in change that could potentially be predicted with the addition of other variables into subsequent models.

It is important to note that these two models are successive; the variance components of the unconditional growth model cannot be directly compared to the variance components of the unconditional means model because the addition of the three TIME variables changes the interpretation of the output.

Conditional Models Analyses

Next, we wanted to determine the effect of the variables of enrollment in a service-based section of the course (either as a first or second exposure), the demographic variable of gender, and URM as predictors of both initial status and change. We examine these predictors in order to explain any between-person variation in each individual elevation (intercept) and linear rate of change (slope) seen in the unconditional models. Table 5.5 includes the estimates from these subsequent "fitted" models. From Table 5.5, we can conclude any overall patterns from each individual predictor variable.

In Model C, the impact of service as either the 1st or 2nd section taken by the students did not have a significant predictive impact on students' identity trajectories; however, this model does suggest that students who take the service section after a non-service section do not reach the same levels of identity as their peers. In Model D, gender has a bigger impact on students' identity trajectories, with females decreasing in *Identity* score over time. Model E predicts that URM students will decrease in *Identity* score over the first semester as compared to their peers, while majority students will increase their *Identity* score over time.

While each independent variable along with variable interactions were modeled for impacts on students' identity with engineering as a profession, only two models that practically or significantly added to the overall strength of the analysis are covered in more detail for the rest of this paper.

Model F: Service, gender, and interaction over time

This level 2 model speculates the existence of an average trajectory of the population for each *Gender* (male and female) who either participated in a PBSL section first, second, or not at all. However, the level-2 residuals account for each individual's own true change trajectory. Results that represent this model are shown in Table 5.5.

Figure 5.1 visually represents the change in *Identity* score over time, with respect to service and gender. This figure shows us that Model F predicts that all female and male students began with a similar *Identity* score (restricted range). Females and males who start in an SL section increase at a greater rate over the first semester and then maintain their *Identity* score as compared to their peers. Both females and males who have a SL section as their second offering do not change much in *Identity* score over the year. Lastly, females who participate in two non-SL sections of *Creative Engineering* over the year decrease in *Identity*, while males in two non-SL sections gradually increase in *Identity* score by the end of the year.

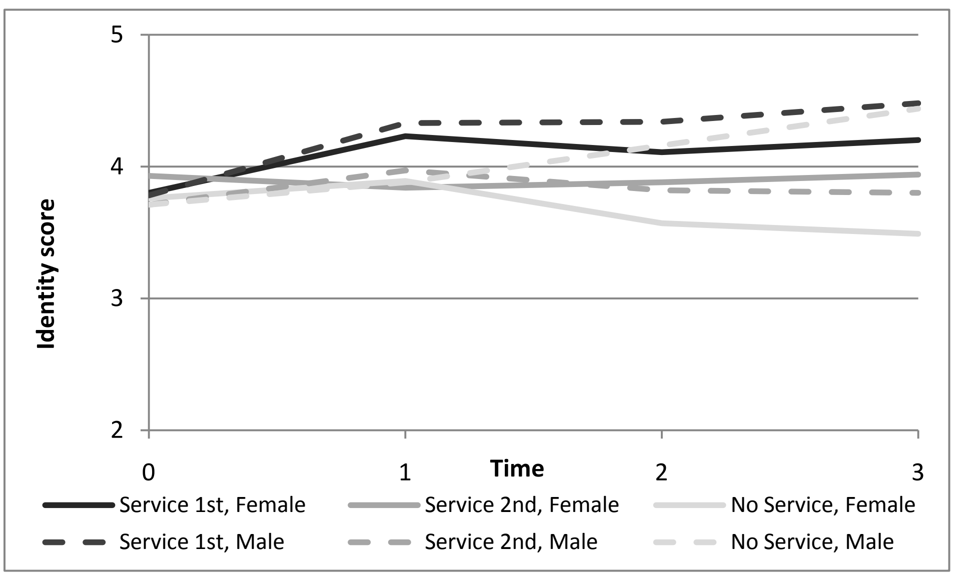

Figure 5.1. Prototypical change trajectories recovered from the HLM analyses for *Identity* score in 63 subjects by service, gender, and their interaction (Model F). Time is reported in test administration, with initial administration at time 0.

In order to confirm the patterns in Figure 5.1 and find the opposite increasing and decreasing pattern between genders from Table 5.4, we took a closer look at the individuals in the cohort of high school students. A residual file was created in HLM and analyzed in SPSS. Empirical Bayes estimates for standard deviation of time were highest for the males who enrolled in an SL section during the second semester (SD = 0.93), suggesting that the variability in slopes is greatest for this group. An examination of the sum of the fitted and residual (EC) means for the cohort resulted in negative mean slopes across the second and third survey administrations for females who had no SL-sections over the year, confirming the predicted pattern of decreasing growth over time for that group in Model F and Figure 5.1. Relative to other female groups, the female students enrolled in no SL-section over the year had the largest decrease in slope, also visible in Figure 5.1. An examination of the correlations between EC intercept and slope indicated that, over the entire year, all sub-groups have a general predicted pattern of greatest growth for students with the lowest initial *Identity* scores.

Model G: Service, ethnicity, and interaction over time

This level 2 model speculates the existence of an average trajectory of the population for each underrepresented minority (URM) and majority students who either participated in a PBSL section first, second, or not at all. However, the level-2 residuals account for each individual's own true change trajectory. Again, results that represent this model are shown in Table 5.5.

Figure 5.2 visually represents this change in identity over time in Model G, with respect to service and ethnicity. This figure shows us that Model G predicts that both URM and majority students who start in an SL section increase at a greater rate over the first semester and subsequently maintain their *Identity* score as compared to their peers. Both URM and majority students who have a SL section as their second offering maintain their *Identity* score over the year, however; URM students start with a slightly higher *Identity* score than their peers. Lastly, both URM and majority students who do have no SL-sections show relatively slight increases in Identity score, but do not reach the level of their peers who had an SL section as their first/only offering.

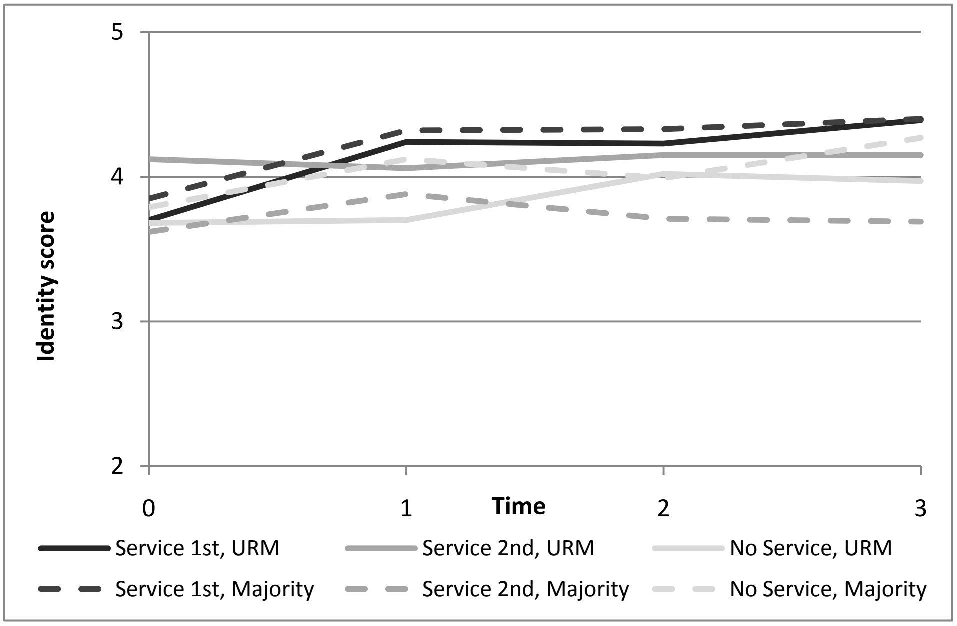

Figure 5.2. Prototypical change trajectories recovered from the HLM analyses for *Identity* score in 63 subjects by service, ethnicity, and their interaction (Model G). Time is reported in test administration, with initial administration at time 0.

In order to confirm the patterns in Figure 5.2, we took another close look at the individuals in the cohort of high school students. A residual file was created in HLM and analyzed in SPSS. Empirical Bayes estimates for standard deviation of time were highest for URM students who enrolled in an SL section as their first/only offering (SD = 1.09), suggesting that the variability in slopes is greatest for this group. An examination of the sum of the fitted and residual (EC) means for the cohort resulted in negative mean slopes across the first survey administration for URM students who had an SL-section second, confirming the predicted pattern of decreasing growth over the first semester for that group in Model G and Figure 5.2. An examination of the correlations between EC intercept and slope indicated that, over the entire year, all sub-groups have a general predicted pattern of greatest growth for students with the lowest initial *Identity* scores.

Pseudo R^2 statistics and Goodness-of-fit

Overall, there was very little change in within-person variance, between-person variance, and covariance from the unconditional growth model. In examining pseudo-R^2 statistics and goodness-of-fit for the identity analyses, all Models maintain a consistent R^2_ε that explains the degree to which adding a growth variable alters the model. This confirms that the addition of any predictor variables to the level-2 model helps to explain the model without altering the original growth model. In examining R^2_o statistics, no Models really provide much further explanation (R^2_o <0.06 or 6%) in defining the initial status of participants in the study. Also all Models have relatively low R^2_1, R^2_2, and R^2_3 (R^2<0.11), indicating that there is little further explanation of the variation in rates of change in the model. In other words, no Models provide substantial explanation in defining the rate of change in the model beyond the conditional growth model. Lastly, Models F and G display the largest decreases in Deviance while still having low penalties on the relative goodness-of-fit (due to the number of parameters in the model), indicating that considering SL along with gender or ethnicity may have the best predictive impact on the outcome of our data.

Limitations of the Study

The findings of these analyses should be placed within the limitations of this study. First of all, the cohort of participants is a small sample and comes from one year of high school students enrolled in a particular course at Skyline High School, which limits the generalizability of the findings. Also, 12 of the students took two sections of the *Creative Engineering Design* course (PBSL and non-service PBL) during the fall 2010 semester. Of these students, four were Hispanic female students, while the remaining eight were majority male students. We analyzed the predictive impacts of our model with respect to "doubling" and found no considerable impacts for this group. For the purposes of this paper, those twelve students were lumped back into the cohort and considered with the group that enrolled in a SL section during their first/only semester, since they did engage with a real local service-based client during the semester. Small focus group results indicated that female students who "doubled" indicated a preference for the PBSL section of the course.

Grades for all students in these classes were relatively high, since the intent of the course was to encourage students into engineering. Grades were lowered for the few students who did not complete assignments or fully participate in class. Therefore, data on grades was not useful in differentiating student learning between sections of the course.

Although the course was taught by two separate instructors, anecdotal evidence indicates that both teachers are highly regarded by students. The teachers also worked closely together on a daily basis on the course, shared an office space, and sometimes engaged in each other's classes.

Small focus groups indicated that students cross-talked to each other about the sections. It was evident that many students were also excited about the projects in the other sections, with no obvious preference for any one topic. Students who did not double were also able to anecdotally list advantages and disadvantages of each type of project. Advantages of the PBSL project that were mentioned included helping out and interacting with an actual client, a sense of accomplishment, and a project that was "real," while disadvantages mentioned included a sense of not wanting to "fail" the person for whom they were creating the product.

Discussion

If we want U.S. engineering to continue to be globally competitive, then we must attract more college-age students to its degree programs; especially students who represent the changing diversity of the U.S. college-aged population. Incorporating PBSL design into K-12 classrooms to increase pre-college exposure to engineering may capture the interest of a diverse population of students, including women and minorities, into engineering undergraduate careers and future STEM workforce. This paper examines the impact of PBSL on students engaged in an existing high school STEM Academy and engineering design course.

For this cohort of high school students, there was an increase in identity with engineering as a result of exposure to PBL engineering design during their *Creative Engineering Design* course offerings. However, we discovered smaller increases in overall female self-reported mean *Identity* scores and larger increases in self-reported mean *Identity* scores for students considered minorities in engineering disciplines. A service-learning context had the largest practical impact on change in *Identity* for students who engaged in an SL-project during the first/only semester of the design course. We noticed a "ceiling effect" where some students start with the highest score on self-perceptions of identity and stayed there throughout the year.

We focused our analysis on a "restricted range" of students without an initially high identity, which represents the fraction that is it likely most important to impact because they might not otherwise choose to major in engineering in college. Using an HLM method, we were able to investigate the impact of SL on the identity with engineering of these students, particularly females and underrepresented students. Although not statistically significant due in part to small sample sizes, a closer look at these predicted change trajectories provided interesting patterns in subsets of students, including:

- The female students not enrolled in any SL-sections over the year had the largest decrease in self-reported *Identity score*, while females who start in an SL section increase at a greater rate over the first semester and then maintain their *Identity* score as compared to their peers. Both of these results indicate that there may be some impact of PBSL in negating significant decreases in engineering identity over time for female students.
- Males, who had either SL as their first/only section during the year had a predicted quicker growth than their peers. This suggests a potential benefit of a PBSL context across genders.
- Our analysis predicted greater change in slopes over the year for URM students engaged in SL as their first/only offering, which suggests that PBSL may have a positive impact on URM students at the K-12 level.
- Majority students who also start in an SL section increase in identity at a greater rate over the first semester and subsequently maintain their *Identity* score as compared to their peers. This suggests that PBSL can benefit students across ethnicities.
- All sub-groups of students have the same predicted pattern of high growth for initially lower *Identity* scores. This supports PBL as an instructional method to increase students' identity with engineering, with or without an SL context.
- Overall, the greatest decreases in *Identity* score were for female students not engaged in any SL section over the course of the year.

This study indicates that PBSL projects in pre-college courses can potentially foster deeper connections with other engineering students and identity with engineering. Through the engineering-focused Skyline STEM Academy, students are engaged during the school day, making science, technology, engineering, and math part of their day to day world. In fact, the program is already impacting the undergraduate choices of its students, with 8 out of 10 current seniors (who had only 3 possible years of engineering through the STEM Academy) applying directly to engineering at the University of Colorado Boulder. Of those 8 students, 4 have been directly admitted to engineering thus far (with 2 more under consideration); 3 of those 4 directly admitted are women; and 3 of those women have confirmed. As we continue to survey the high school students with respect to their identity with engineering, we will grow the data set to include attitudes and intent across multiple cohorts and years. It will be interesting to follow these STEM Academy students after four possible years in the program to see if the patterns persist and even more Academy graduates move into engineering undergraduate programs.

Using a method of practicing engineering in a community context, partnered with a strong emphasis on teamwork and reflection, PBSL programs may be effective approaches to recruit and retain engineering students (Bielefeldt et al., 2009; Sullivan & Zarske, 2005). We conclude that the opportunity to engage in pre-college engineering that is meaningful and relevant, specifically using a SL context, has the potential to impact the interest and recruitment of quality STEM-prepared high school students, including women and minority students, into the pipeline of engineering education and the engineering workforce. Based on the results of this study, K-12 and undergraduate institutions seeking to increase diverse students' identification with engineering should consider PBSL engineering design experiences early and often.

CHAPTER VI

COMMUNITY SERVICE ATTITUDES OF HIGH SCHOOL AND FIRST YEAR ENGINEERING STUDENTS IN PROJECT-BASED DESIGN COURSES

Introduction

The idea of service learning has been around since the 1860's, with the establishment of land-grant universities focused on agriculture and mechanics in the United States. Each land-grant university had a requirement of service to the community as part of its mission (Lima & Oakes, 2006). Service-learning (SL) is an educational method through which students actively participate in community service as an integral component of their coursework, fostering both civic responsibility and scholastic abilities through the integration of academic instruction and community-based service. The needs of the community define the service tasks for the students, providing students with the sense of responsibility for being members of a larger community and shifting their perceptions and commitment towards others and service-oriented careers (Jacoby & Associates, 1996; S. R. Jones & Abes, 2004). Students begin to understand that they can use what they learn in SL experiences to "make the world a better place" (Reeb, Folger, Langsner, Ryan, & Crouse, 2010).

At its core, SL courses include partnerships in and around the community (often with disadvantaged populations), promoting mutual learning of students and community participants in complex settings that encourage problem solving and reflection (Lemons et al., 2011; Lima & Oakes, 2006). SL courses have been well-established in the social sciences, and are evolving in engineering colleges as a mechanism to elevate student communication skills and provide engineering students with meaningful learning experiences (Sullivan & Zarske, 2005; Tsang, 2000c). Within engineering, SL is frequently integrated into hands-on problem or project –based courses. More commonly referred to as project-based service-learning (PBSL), these courses are appearing increasingly at universities who wish to help their students bolster learning of design skills by solving real-world projects. The combination of service-learning and project-based learning provides engineering undergraduates an opportunity for individual growth in cognitive, social, and moral levels concurrently, leading to a greater maturation of the whole self (Bielefeldt et al., 2010).

SL can also potentially increase the practice of professional ethics in engineering, an area that is sorely lacking in today's undergraduate curricula (Fleischmann, 2003). Ethical and societal considerations are desired characteristics of engineering graduates, according to ABET and other professional societies; however, students need more training in these areas if they are to meet the needs for innovation in our increasingly global marketplace (ABET, 2011; NSPE, 2010; The Body of Knowledge Committee of the Committee on Academic Prerequisites for Professional Practice, 2008). Professional engineers also recommend that students be engaged in learning more critical thinking skills that encourage them to analyze, design, and implement solutions to problems, similar to workforce expectations (Goel & Sharda, 2004). However, this is still not a common thread in many engineering education programs. More flexible problems, in a SL context, that do not have one "right answer" offer a potential means to meet these multiple objectives.

Overall, students seem favorable towards engaging in community-based service activities and perceive greater connection to civic responsibility and benefits to learning when engaged in real-world problem-solving experiences (Y.-J. Chang, Wang, Chen, & Liao, 2010; Pritchard, 1999; RMC Research Corporation, 2002). Unfortunately, there is not enough research on student disposition and developing attitudes towards community service in engineering programs at the K-12 and undergraduate levels to understand how effectively engaging in these experiences may help attract and retain students in engineering while also creating well-prepared engineers.

This paper examines the developing attitudes towards community service for both high school and first-year college engineering students. Specifically, we observe the change in community service attitudes for a cohort of high school and first-year engineering students engaged in project-based design courses and whether a service-learning context or gender influences these changing attitudes.

Review of Literature on Service, Ethics, and Engineering Education

There has been a call for more rigorous review of ethics in professional engineering settings and from engineering professional societies (Durbin, 2008). ABET criteria requires that graduates have an understanding of professional and ethical responsibility (3.f) as well as an understanding of the impact of engineering in global and social context (3.h) (ABET, 2011). However, engineering in public service is complex, with engineers required to simultaneously make (sometimes conflicting) ethical choices around individual, professional, and societal levels (Emison, 2006). Unfortunately, one study found that less than 27% of all engineering institutions have a required ethics course for engineers (Fleischmann, 2003).

As a response, the question of how to integrate engineering ethics and authentic design experiences into undergraduate curricula has become an ongoing topic of interest. Incorporating SL into engineering coursework presents a promising solution for meeting these ABET outcomes. Historically, much of engineering ethics focuses on wrongdoing and failures, however there is a positive side that focuses on engineers obligations to become a contributing member in the workplace and society (Pritchard, 1999). The National Society for Professional Engineers

(NSPE) and American Society for Civil Engineers (ASCE) include language that states broadly that service to the community is an important part of engineering ethics, and the ability to analyze the impacts of engineering on public health, safety, and sustainability are an essential part of the skill set for future engineers (NSPE, 2010; Pritchard, 1999; The Body of Knowledge Committee of the Committee on Academic Prerequisites for Professional Practice, 2008). Engaging in SL not only helps students understand the impact of engineering solutions in a global and societal context but working directly with a community client can help reinforce professional and ethical responsibility, nurturing a more responsible engineer in the workplace and community (Bielefeldt et al., 2010; Pritchard, 1999). Several papers have argued for ethics integrated throughout the entire undergraduate curricula and an increase in SL projects in direct contact with local community client as a vehicle to enhance students' ethical understanding and responsibility towards community service (Fleischmann, 2003; Pritchard, 1999). Students in SL find themselves discussing ethical considerations of their projects similar to those that they will encounter in the workplace, meeting both ABET ethics and societal impacts criteria (Pritchard, 1999).

SL in the classroom has additional reported benefits as well, helping create an overall well-rounded learning experience for students. With the recent attention to identifying the educational and psychological outcomes associated with SL, current undergraduate programs are driven to include engineering skills and attitudes considerations in their program assessment (Harding et al., 2010). Studies across multiple universities and disciplines have found positive benefits of SL in the classrooms on: academic learning of technical subject matter, personal and interpersonal skills development, self-perception of ability to make significant changes in society using what they have learned, increased interest in volunteering and civic engagement, a shift in focus towards helping others, and overall self-efficacy (Astin et al., 2000; Bielefeldt et al., 2009; Canney & Bielefeldt, 2012; Duffy et al., 2009; Freeman, 2011; Harding et al., 2010; S. R. Jones & Abes, 2004; Lemons et al., 2011; McFadden & Maahs-Fladung, 2009; Seider et al., 2011). Undergraduate students find the service aspect rewarding; personal engagement in the project increases their emotional understanding of the problem that needs to be solved leading to a motivation to accomplish their project as best they can (Y.-J. Chang et al., 2010; Pritchard, 1999). Pre-college students also support community service and required civics courses in middle and high school (Lopez, 2002). The research at the K-12 level indicates similar benefits from participation in SL, including: increased attendance, motivation to learn, academic achievement, attitudes towards school and civic engagement, and leadership skills, ultimately creating more active members of society with respectful attitudes towards others in diverse groups, an awareness of social issues, and a deeper connection to their community (RMC Research Corporation, 2002; Webster & Worrell, 2008). An extensive review of over 50 studies by the National Service-Learning Clearinghouse (2002) on SL in K-12 settings (from elementary to high school) shows promise for SL to increase achievement among at-risk students (17 studies), an increase in civic engagement (21 studies), and an increase in social-emotional skills such as self efficacy, confidence, and collaboration skills (21 studies) (RMC Research Corporation, 2002).

Offering a PBSL oriented curriculum may expand the appeal of engineering to a broader population in addition to the aforementioned increase in student abilities for those already engaged in engineering. Retaining the interest of women and students of color in engineering is reported to improve at both the K-12 and undergraduate levels when subject matter is placed in a social context and cooperative, interdisciplinary approaches to problems focus on holistic and global impacts (Matyas & Malcolm, 1991; Mihelcic et al., 2008; Noddings, 1992; J. Oakes et al., 1992; Seider et al., 2011; Zimmerman & Vanegas, 2007). SL research at the K-12 level indicates that a service-learning context may be a key factor in the recruitment of minority and female students into engineering offerings (M. Thompson et al., 2008). Several undergraduate programs report that the opportunities to engage in service-learning was a factor in selecting the program, with research conducted at the University of Massachusetts, Lowell, finding that consistently over 60% of students surveyed from year to year indicating that engagement in service-learning caused those students to stay in engineering (Coyle et al., 2003; Duffy et al., 2009; Fisher et al., 2005; West et al., 2010). Specifically, PBSL has been reported to positively impact first-year students' perceptions of their roles as engineers and satisfaction with their first year-experience (Coyle et al., 2003; Harding et al., 2010). Showing students the broader impacts of engineering on society and allowing them to make immediate positive contributions using their new engineering skills has already been confirmed as more attractive to underrepresented students; especially women (Hokanson et al., 2007; Moskal et al., 2008).

Overall, there may actually be an overrepresentation of women in the SL-based courses and programs as females have more positive attitudes towards SL and even volunteer to participate in SL at a higher rate than their male counterparts (Bielefeldt et al., 2008; Coyle et al., 2003; Duffy et al., 2009; Freeman, 2011; Matusovich et al., 2006; Mihelcic et al., 2008; Seider et al., 2011) 50% of academically talented K-12 adolescents participate in community service, with higher representation of females in organization-based SL (not classroom) than males (Webster & Worrell, 2008). In fact, despite the uniformly positive attitudes towards community service across ethnicity, grade level, and SES, the typical profile for SL participants in high school is white female (Webster & Worrell, 2008).

Although increased service to the community has been suggested to enhance students' ethical and societal responsibility, and broaden the appeal of engineering to a wider audience, there is little supporting literature to help researchers and educators fully understand how student attitudes towards service change over time. Conceivably, students that have an inclination towards service may be better able to understand the ethical and societal implications of their actions and experiences. Several researchers have questioned the effectiveness of SL based on the predisposition of students towards service when entering the course, and attitudes towards service need to be measured in order to predict student intentions to engage in community service beyond the classroom (Bauer, Moskal, & Gosink, 2007; Shiarella, McCarthy, & Tucker, 1999) Several surveys have been developed that intend to assist in this process. The Community Service Attitudes Scale (CSAS), based on Schwartz's altruistic helping behaviors model, measures a person's awareness of a need for community service, belief that they are morally obligated to act on that awareness, evaluation of costs and benefits from service activity, and overt action response (Bauer et al., 2007; Shiarella et al., 2000) The Community Service Self-Efficacy Scale (CSSES) measures a person's confidence in their personal ability to make meaningful contributions to society through service, considered to be a core characteristic of a civic-minded college graduate (Reeb et al., 2010). Interestingly, both surveys have found that female students show a consistent tendency to score higher than their male counterparts, indicating that attitudes towards service may be one area where females beat out males despite other research that concludes males have greater general self efficacy than females (Reeb et al., 2010; Shiarella et al., 2000). These results may be a bit preliminary, since subsequent research has found few if any significant differences in the community service attitudes of engineering students based on gender (Bauer et al., 2007; Bielefeldt et al., 2008). CSAS scores were also previously found to correlate college major (social work majors highest, followed by psychology; business majors the lowest), community service experience (more previous experience a higher score), and intent to engage in community service (Shiarella et al., 1999).

Participating in engineering projects for social good (such as PBSL projects) or other non-engineering service work has a positive impact on competence, helping students become potentially more responsible engineers, socially responsible citizens, and benefiting the community at the same time (Duffy et al., 2009; Freeman, 2011; Palmer et al., 2011). However, it is imperative to better understand how students' attitudes towards service to the community develop, and if a predisposition to service impacts how the students learn from their SL experience. While there is a strong movement for including SL in engineering curricula at both the K-12 and undergraduate level to increase students' understanding of and ethical obligation to society, there is a need for more literature to help us understand the service-based attitudes of students before and as a result of engaging in SL.

Research Questions

This study examines the attitudes towards community service in K-12 and first-year engineering students. Specifically, we explore the following research questions in this paper:

1. Do engineering K-12 and undergraduate students engaged in project-based design during their first semester of study change their attitudes towards community service over time?
2. Are there differences in attitudes towards community service between high school students and first-year engineering undergraduates?
3. Does a relationship exist between students' community service attitudes and a service-learning context in an engineering design course or gender?

Methods

Setting

The setting for the implementation of our research questions has been described at length in previous articles (Zarske, Reamon, et al., 2012; Zarske et al., 2012). In brief, we engaged two populations of engineering students in this study. Both courses have multiple sections per semester, offering a variety of topics from foundational mechanical designs to service-based designs for actual clients.

1. The 10th grade *Creative Engineering Design* course at Skyline High School in Longmont, Colorado is just one offering in their popular STEM (science, technology, engineering, and math) Academy that bring hands-on STEM experiences to students starting in 9th grade, with a goal of retaining students at-risk of early school dropout. The semester-long *Creative Engineering Design* course immerses student teams in a project-based engineering design process, encouraging teamwork and communication, and resulting in the development of a final prototype product. Students are aware of the general section topics prior to registration, resulting in sections filling with students based on interest and timing of other required courses. For the fall 2010 semester, topic choices included one section of Assistive Technology (Robotics), one section of Biotechnology (service-learning for a local community client), and two sections of Structural Design (Cranes). Approximately 21% of the sophomore class are enrolled in STEM and took the *Creative Engineering Design* course, along with a small number of 11th graders who were not able to take the course the previous year.
2. The *First-Year Engineering Projects* (FYEP) course at the University of Colorado Boulder engages students in an interdisciplinary, hands-on design-build experience that

encourages collaboration and time management for teams of students creating innovative prototype engineering products and inventions. Roughly 53% of the incoming class of freshmen is enrolled in the course per year, with several majors required or strongly encouraged to take the course (mechanical, environmental, aerospace, civil and "undecided"). Students enroll in the different sections of FYEP without knowing the specific project topic prior to the start of the semester, resulting in sections filled with a mix of students from different disciplines. For the fall 2010 semester, five sections were challenged with service-learning projects (such as assistive technology, products for local low-income community partners, or health games) and the five other sections engaged in non-service-learning projects (such as, robotics, water systems, and Rube Goldberg machines).

Participants

The analysis in this report contains survey data from 82 10^{th} and 11^{th} grade students enrolled in 10th grade *Creative Engineering Design* during the fall 2010 semester, as well as data from 272 FYEP engineering students enrolled in ten sections of FYEP during the fall 2010 semester. Their demographic distributions are summarized in Table 6.1.

Table 6.1. Demographic distributions of high school and first-year students participating in the study during the fall 2010 semester (number and percent, where appropriate).

K-12 Students	**N**	**%**	**FYEP students**	**N**	**%**
Overall	**82**		**Overall**	**272**	
Female	26	32%	Female	68	25%
Male	56	68%	Male	204	75%
Service	23	28%	Service	139	51%
Non- service	59	72%	Non Service	133	49%
# Sections	3		# Sections	10	
# Instructors	2		# Instructors	10	
# Instructors (service sections)	1		# Instructors (service sections)	5	

Assessment Instrument

Students were given an online engineering attitude survey during class in the first and final weeks of the fall semester, with choices on a five-point Likert-type scale for each survey question ranging from "not at all" to "definitely." Students typically completed the survey instrument within ~15-20 minutes. Both surveys contained items aggregated from various sources, with the goal of measuring the change in several different theory-based constructs over the semester. These sources include the Persistence in Engineering Survey (PIE), the Engineering Identity Survey, and the Community Service Attitudes Scale (Chachra et al., 2008; Eris et al., 2010; Shiarella et al., 1999). The measured constructs differed slightly between high school and undergraduate groups based on our research interests at both levels, and the survey items at each level were examined for high inter-item reliabilities and subsequent factor loading.

This paper focuses on 15 survey items adopted from the Community Service Attitudes Scale (CSAS), which assesses the degree of participants' attitudes regarding community service (Shiarella et al., 2000). The full CSAS instrument includes 34 items and was found to be reliable and valid (Shiarella et al., 1999). The 34 items fell into 10 different sub-scales, and questions from four of the sub-scales were used (awareness, connectedness, norms, and intent). In addition, demographic data on gender was collected, and missing values were retrieved from transcript data and administrative records. Surveys for all participating students are conducted under the University of Colorado Boulder's Institutional Review Board (IRB) approval, reviewed annually by external and internal evaluators. Student responses were coded to protect participant identity.

A Principal Components Analysis (PCA) was performed to analyze the theoretical constructs represented by the sets of response items in each survey and to determine how well the items measure the concepts that we intended. For the FYEP survey, the 15 CSAS items factored out independently from the other survey items, confirming that we included a single, measurable dimensionality of attitudes towards community service. On the high school version of the survey, only 12 of the 15 CSAS items factored out into a single measurable dimensionality, with three items belonging to the original CSAS awareness sub-scale forming a separate factor with seven other survey items related to awareness of engineering contributions to society. Additionally, one survey item that we intended to assimilate with other efficacy questions, "I can identify the particular wants and needs of a local customer," factored in with our community service items (total items=13). The high school survey PCA also suggested community service may correlate significantly with students' awareness of engineering contributions, though not very strongly (r=0.30).

Since both PCA analyses resulted in a strong, multiple (over 10) item factor representing attitudes towards community service, the average of the items that loaded on each *Community Service* factor is used as the independent variable in the remainder of this analysis. However, comparisons between the high school (n=12 CSAS plus one other items) and FYEP (n=15 CSAS items) attitudes do not represent the exact same questions (FYEP includes three additional questions related to an awareness of the needs that can be met by engineering contributions). Example survey items for the *Community Service* factor are presented in Table 6.2.

Table 6.2. Survey Items for *Community Service* in the *Creative Engineering* and FYEP surveys

Factor and Example Constituent Items
Attitudes towards Community Service (Shiarella et al., 2000)
Pretend you are going to volunteer for community service sometime in the next year. Rate how you feel about the following.
Improving communities is important to maintaining a quality society.
I am responsible for doing something about improving the community.
I feel an obligation to contribute to the community.
Other people deserve my help.
It's my responsibility to take some real measures to help others in need.
I will seek out the opportunity to do community service in the next year.

Statistical Analysis

Our statistical approach has also been described in previous chapters. The average of the 1-5 Likert-scale responses that loaded on the *Community Service* factor for each group is used to represent the independent variable and paired pre- to post- for each individual. First, we analyzed the data for missing values and data entry errors. Two 10th grade students and twenty FYEP students who did not complete either a pre- or post- survey were examined for patterns and excluded from the data set prior to analysis. Missing survey data was handled during subsequent analyses with listwise deletion. Missing demographic data was retrieved from high school and university administrative records.

We initially examined descriptive statistics on our variables of interest, including comparisons of our pre-survey mean scores with previous studies found in the literature. Due to a change from the seven-point Likert scale on the original CSAS survey to the five -point Likert scale on the current survey, we can only make superficial comparisons to previous mean scores on individual items. However, patterns of mean scores between the different CSAS administrations may prove valuable. Paired-samples t-tests were used to analyze the within-person differences in factor scores over the course of the semester. The resulting paired sample correlations indicate that students who scored higher on the pre-survey also scored higher on the post-survey. For these analyses, IBM SPSS statistical software package (version 20) was used.

Next, we developed a hierarchical linear model (HLM) to further estimate both course- and individual-level effects on our variables of interest for each of the *Creative Engineering* and FYEP cohorts. HLM affords the researcher some flexibility in representing relationships between variables on different levels (such as individual-level and course-level) (Raudenbush & Bryk, 2002). In this type of modeling, the researcher first develops a level-1 model that describes the intercept and rate of change (time) for an individual within the overall cohort (using an unconditional means model and an unconditional growth model, described below), and then develops level 2 models that represent the hypothesized effects on how the level-1 individual intercept and growth parameters are related to between-subject factors, such as service and gender. We used a full maximum likelihood (FML) estimation method that considers all the population parameters that maximize the likelihood of observing the sample data. All analyses were run with Hierarchical Linear and Nonlinear Modeling (HLM) software, a modeling software distributed by Scientific Software International, Inc.("Hierarchical Linear and Nonlinear Modeling (HLM)," 2011)

Results

Overall Results per Cohort

Initial descriptive statistics showed that both high school and FYEP students start with relatively high mean pre-survey scores on attitudes towards community service (in the top 20% on a scale of 1-5). Interestingly, the initial mean scores for the high school and FYEP cohorts are also very similar to the scale-adjusted mean scores averaged from the four CSAS sub-scales found in previous studies by Shiarella, Bielefeldt, and Bauer (see Table 6.3) (Bauer et al., 2007; Bielefeldt et al., 2008; Shiarella et al., 1999). This suggests that aggregated student attitudes towards four community service sub-scales (awareness, connectedness, norms, and intent) remain consistent across several studies.

Table 6.3. Comparison of scale-adjusted mean scores averaged from the four CSAS sub-scales found in previous studies.

Group surveyed	n	% female	Overall mean CSAS score
Zarske High school students Longmont, Colorado 2010	82	32	4.3
Zarske First year engineering undergraduates University of Colorado Boulder 2010	272	25	4.2
Bielefeldt Environ. Engineering first year undergraduates University of Colorado Boulder 2006	29	48	4.1*
Bielefeldt Environ. Engineering seniors University of Colorado Boulder 2006	17	35	4.1*
Bielefeldt Undergraduate and graduate engineering students University of Colorado Boulder 2007	11	~60	4.3*
Bauer Undergraduate engineering students Colorado School of Mines 2004	78	~13	3.7*
Shiarella Undergraduate business, psychology, communication and education students A Western univrsity 1997	332	59	4.0*

Notes: Cell entries contain initial mean scores from this work compared to the average of the CSAS sub-scales of awareness, connectedness, norms, and intent scaled to the 5-point Likert scale from other published studies (scaled from 7 pt Likert using average CSAS score*5/7); Results retrieved from (Bauer et al., 2007; Bielefeldt et al., 2008; Shiarella et al., 1999)

An independent samples t-test was run on pre-survey scores to find any significant differences between sub groups. For the high school cohort, there was a significant difference in pre-survey scores between students enrolled in the SL or non-SL sections (p=0.04), but no significant difference by gender (p=0.64). This confirms that students who elected to enroll in the SL section scored higher on community service attitudes than their peers in non-SL sections. The FYEP students had no significant differences in pre-test scores by service (as expected since the

SL nature of a section was unknown when the students enrolled), but a significant difference in pre-test scores by gender ($p<0.001$). This confirms that female students in FYEP scored higher than males on community service attitudes, similar to previous research using CSAS by Shiarella (Shiarella et al., 1999).

Further data screening generated descriptive statistics that showed trends over time for the overall cohorts of high school and FYEP students (see Table 6.4). A paired-samples t-test was used to analyze the within-person differences in factor scores over the course of the semester. The pre- to post-mean scores of the overall high school students, as shown in Table 6.4, demonstrate a small increase in attitudes towards community service. The largest increases were for female students, and particularly for female students in non-service PBL sections. This is surprising until you notice the extremely high (on a scale of 1-5) score for females in general, suggesting a possible "ceiling effect" for groups of students (some students maintain a high score pre- to post- semester). This is consistent with previous studies that noticed a similar ceiling effect for college students with high pre- CSSES scores (Reeb et al., 2010). It is also interesting to note that almost all students start with a relatively high attitude towards community service at the start of the semester (score>4), consistent with the literature that high school students are already favorable towards participation in community service (Lopez, 2002; RMC Research Corporation, 2002).

The cohort of FYEP students also displays a relatively strong initial level of community service attitudes. This similarity to high school students is not overly surprising, since these particular students are just in their first semester out of high school. There is a little variation in mean difference in score by gender or enrollment in a SL-section of the course, with the largest increases for males and males in non-service sections in particular. This reflect the prior research that indicates little difference towards service activities by gender using the CSAS instrument with undergraduate engineering students (Bauer et al., 2007; Bielefeldt et al., 2008).

Table 6.4. Descriptive statistics for *Community Service* in overall cohort of high school and FYEP students.

	N	Pre Survey Mean (SD)	Post Survey Mean (SD)	Mean Difference
High School Creative Engineering				
Overall	**82**	**4.31 (0.52)**	**4.40 (0.57)**	**0.09***
Service - All	23	4.50 (0.43)	4.57 (0.53)	0.07
No Service - All	59	4.24 (0.54)	4.34 (0.57)	0.10*
Females-All	26	4.35 (0.39)	4.50 (0.36)	0.15~
Males- All	56	4.29 (0.58)	4.36 (0.64)	0.07
Service - Females	9	4.54 (0.21)	4.55 (0.45)	0.01
No Service - Females	17	4.25 (0.42)	4.48 (0.32)	0.23~
Service - Males	14	4.48 (0.54)	4.58 (0.59)	0.10
No Service - Males	42	4.23 (0.58)	4.29 (0.64)	0.06
First-Year Engineering Projects				
Overall	**272**	**4.23 (0.63)**	**4.30 (0.66)**	**0.07***
Service -All	139	4.24 (0.62)	4.31 (0.69)	0.07
No Service - All	133	4.22 (0.65)	4.30 (0.64)	0.08~
Females-All	68	4.52 (0.57)	4.54 (0.56)	0.02
Males- All	204	4.14 (0.63)	4.23 (0.68)	0.09*
Service- Females	33	4.53 (0.51)	4.55 (0.52)	0.02
No Service - Females	35	4.52 (0.63)	4.53 (0.60)	0.01
Service-Males	106	4.15 (0.63)	4.24 (0.72)	0.09
No Service -Males	98	4.12 (0.63)	4.22 (0.63)	0.10*

Notes: Cell entries contain mean scores and standard deviations for student participation, by gender and service-learning context.
~ $p<0.10$, * $p<0.05$ level, paired t-test

Unconditional Model Analysis

We developed both an unconditional means model (Model A) and an unconditional growth model (Model B) for each cohort of students in the study (see Tables 6.5 and 6.6). These models look across participants to determine if there is enough variation to deserve further investigation. The unconditional means model estimates the average elevation of the true individual change trajectories (represented by β_{0x}) without regard to time, while the unconditional growth model adds a predictor variable of time and examines the elevation and linear rates of change (slope) for the outcome variable *Community Service* across participant's entry and time the study. Model B creates a baseline model for change over time and differs from Model A by examining the scatter of each person's scores around their linear change trajectory instead of their mean intercept with an assumed flat trajectory.

The estimated average elevations in Model A for *Creative Engineering* and FYEP differed significantly from 0 ($\beta_{00} = 4.36$; $p<0.001$ and $\beta_{00} = 4.27$; $p<0.001$, respectively), confirming that the initial score across participants is non-zero. From the unconditional means Model A, we conclude that the score varies over the duration of the study and that the individuals differ from each other. The estimated average elevations in Model B for *Creative Engineering* and FYEP also differed significantly from 0 ($\beta_{00} = 4.22$; $p<0.001$ and $\beta_{00} = 4.23$; $p<0.001$, respectively), suggesting that the true individual change trajectory for *Community Service* maintains a non-zero intercept when a time variable is added to the model. Interestingly, and likely as a result of initially high scores in both cohorts, both *Creative Engineering* and FYEP are predicted to start around the same score in the unconditional growth model. The variance in initial status (σ^2_0) also confirms significant variability for prediction at level 2 in subsequent models. The estimated average rate of change for *Community Service* (represented by β_{1x})

differed significantly from 0, and indicated a small change over time for each cohort (β_{10} =0.09, p<0.05 and β_{10} =0.07, p<0.05). The level 2 variance component associated with rate of change was significant, suggesting that there are amounts of variation in change that could potentially be predicted with the addition of other variables into subsequent models.

Table 6.5. Estimates of the fixed-effects of intercept and slope (β) and variance components (σ) from various models of inter-individual differences in *Community Service* (CS) score in 82 10th grade *Creative Engineering* participants over the course of the study, with standard deviations in parentheses.

			Model A Unconditional Means	**Model B** Unconditional Growth	**Model C** Growth by Service	**Model D** Growth by Gender	**Model E** Growth by Service & Gender
Initial Status, π_{0i}	Intercept		4.36***	4.22***	4.13***	4.23***	4.17***
		β_{00}	0.06	0.08	0.10	0.10	0.11
	Service				0.31~		0.22
		β_{01}			0.18		0.25
	Gender					-0.03	-0.15
		β_{02}				0.18	0.22
	Service* Gender						0.29
		β_{03}					0.35
Rate of change,	Intercept			0.09*	0.11*	0.07	0.06
		β_{10}		0.04	0.05	0.05	0.05
	Service				-0.04		0.04
		β_{11}			0.11		0.15
	Gender					0.09	0.17
		β_{12}				0.10	0.12
	Service* Gender						-0.26
		β_{13}					0.22
Variance components							
Level 1:	Within person, ε_{ij}		0.09	0.00	0.00	0.00	0.00
		σ^2_{ε}	0.30				
Level 2:	In initial status, ζ_{0i}		0.21	0.55	0.53	0.55	0.53
		σ^2_0	0.46	0.09	0.08	0.09	0.08
	In rate of change, ζ_{1i}			0.16	0.16	0.16	0.16
		σ^2_1		0.03	0.03	0.03	0.03
	Covarianc e between			-0.22	-0.22	-0.22	-0.21
		σ_{01}		0.04	0.04	0.04	0.04
Pseudo R^2 Statistics and							
	R^2_{ε}			1.00	1.00	1.00	1.00
	R^2_0				0.00	0.08	0.08
	R^2_1				0.00	-0.50	0.00
	Deviance		209.59	204.24	199.65	202.88	196.85
	AIC		215.59	214.24	213.65	216.88	218.85
	BIC		508.41	642.01	728.94	732.17	849.08

~p <0.10; * p <0.05; ** p <0.01; *** p <0.001

Table 6.6. Estimates of the fixed-effects of intercept and slope (β) and variance components (σ) from various models of inter-individual differences in *Community Service* (CS) score in 272 FYEP participants over the course of the study, with standard deviations in parentheses.

			Model A Unconditional Means	**Model B** Unconditional Growth	**Model C** Growth by Service	**Model D** Growth by Gender	**Model E** Growth by Service & Gender
Initial Status, π_{0i}	Intercept	β_{00}	4.27***	4.23***	4.22***	4.14***	4.12***
			0.04	0.04	0.06	0.04	0.06
	Service	β_{01}			0.02		0.03
					0.08		0.09
	Gender	β_{02}				0.38***	0.39***
						0.08	0.12
	Service* Gender	β_{03}					-0.02
							0.17
Rate of change, π_{1i}	Intercept	β_{10}		0.07*	0.08*	0.09*	0.10*
				0.03	0.04	0.04	0.05
	Service	β_{11}			-0.01		-0.02
					0.06		0.07
	Gender	β_{12}				-0.07	-0.09
						0.06	0.08
	Service* Gender	β_{13}					0.03
							0.12
Variance components							
Level 1:	Within person, ε_{ij}	σ^2_ε	0.13	0.00	0.00	0.00	0.00
			0.01				
Level 2:	In initial status, ζ_{0i}	σ^2_0	0.29	0.40	0.40	0.37	0.37
			0.03	0.03	0.03	0.03	0.03
	In rate of change, ζ_{1i}	σ^2_1		0.25	0.25	0.25	0.25
				0.02	0.02	0.03	0.02
	Covariance between ζ_{0i} and ζ_{1i}	σ_{01}		-0.11	-0.11	-0.10	-0.10
				0.02	0.02	0.02	0.02
Pseudo R^2 Statistics and Goodness-of-Fit							
	R^2_ε			1.00	1.00	1.00	1.00
	R^2_0				0.00	0.08	0.08
	R^2_1				0.00	-0.50	0.00
	Deviance		892.62	885.93	885.85	866.46	866.25
	AIC		898.62	895.93	899.85	880.46	888.25
	BIC		1191.44	1323.70	1415.14	1395.75	1518.48

~p<0.10; * p<0.05; ** p<0.01; *** p<0.001

It is important to note that these two models are successive; the variance components of the unconditional growth model cannot be directly compared to the variance components of the unconditional means model because the addition of the three TIME variables changes the interpretation of the output. These models support the examination of additional predictor variables.

Conditional Models Analyses

Based on the literature, we chose the variables of enrollment in a service-based section of the course, the demographic variable of gender, and a combination of these as potential predictors of both initial status and change. We examine these predictors in order to explain any between-person variation in each individual elevation (intercept) and linear rate of change (slope) seen in the unconditional models. Tables 6.5 and 6.6 include the estimates from these subsequent "fitted" models and help us to establish overall patterns from each individual predictor variable.

The greatest impact by a single predictor variable in the high school data is service (Model C), which predicts that students in service sections will start with a higher score than their peers in non-service sections (β_{01}=0.31, p<0.10). This is likely due to the ability of students to choose into which section topic they enroll. As expected with the ceiling effect mentioned earlier, students in the service sections who start out at a higher score than their peers are predicted to have a slight, non-significant decreases in score over time (β_{11}=-0.04 points over the semester). For the high school students, gender has very little impact on the model (Model D), with females predicted to have an initial starting score barely lower than males (β_{02} =-0.03) and a slight increase in score over time (β_{12}=0.09 points over the semester). The predicted trajectories by gender are not significant.

There was an opposite impact by single predictor variables in the FYEP analysis. For this set of data, service (Model C) does not have any significant predictive impact on students' *Community Service* trajectories. The lack of service impact as compared to the high school data might reflect the inability for FYEP students to choose project topics; they enroll in section of the course without knowledge of the specific project topic prior to the start of the semester. Instead, gender (Model D) has a bigger impact on FYEP students' community service attitudes, with females starting at a higher score than the males (β_{02} =0.38, p<0.001). This is supported by previous research involving the CSAS scale, could reflect a greater sense of responsibility towards the community for females by the start of college (Shiarella et al., 1999). Similar to the service ceiling effect in high school, these females who start high have a predicted slight decrease in score over time (β_{12}=-0.07 points over the semester).

To delve even further into subgroups of students, service and gender were modeled together along with their interactions. The subsequent service-gender models offer a good synopsis of the predicted trajectories for change in *Community Service* score over the course of the semester for 10th grade *Creative Engineering* and FYEP and are covered in more detail for the rest of this paper.

Impact of Service, Gender, and Interaction over Time

This level 2 model speculates the existence of an average trajectory of the population for each *Gender* (male and female) and participation in an SL section of the course over the semester. However, the level-2 residuals account for each individual's own true change trajectory. The resulting equation is given in Figure 6.1, and average elevations and rates of change that represent this model are shown in Tables 6.5 and 6.6.

$$CS_{ti} = \beta_{00} + \beta_{01} *SL_i + \beta_{02} *Gender_i + \beta_{03} *SL\_Gender_i + \beta_{10} *TIME_{ti} + \beta_{11} *SL_i *TIME_{ti} + \beta_{12} *Gender_i *TIME_{ti} + \beta_{13} *SL\_Gender_i *TIME_{ti} + r_{0i} + r_{1i} *TIME_{ti}$$

Where parameters include:

- CS is *Community Service,* the level 1 outcome score of interest (on a scale of 1-5) of individual *i* at time *t* (t= 0 to 1);
- SL is *Service*, a level 2 time-invariant predictor of subject study group (0=non-SL section and 1= SL section);
- Gender is *Gender,* a level 2 time-invariant predictor of subject gender (0=male and 1= female);
- SL_Gender, a level 2 time-invariant predictor that represents the interaction between *Service* and *Gender;*
- TIME is the time at which assessment *t* of subject *i* took place, administered pre- and post- semester and *centered* for each subject's entry into the study at time 0;
– β_{00} is the population average of the level-1 intercepts for individuals with a level-2 predictor value of 0, or population average true initial status for nonparticipants;
– β_{01} is the population average difference in level-1 intercepts, for individuals with a level-2 SL predictor value of 1, or the initial impact of predictor *Service* on initial status;
– β_{02} is the population average difference in level-1 intercepts, for individuals with a level-2 Gender predictor value of 1, or the initial impact of predictor *Gender* initial status;
– β_{10} is the population average of the level-1 slopes, for individuals with a level-2 predictor value of 0, or population average rate of change for nonparticipants;
– β_{11} is the population average difference in the level-1 slope, for individuals with a level-2 SL predictor value of 1, or the impact of predictor *Service* on the individual rates of change;
– β_{12} is the population average difference in the level-1 slope, for individuals with a level-2 Gender predictor value of 1, or the impact of predictor *Gender* on the individual rates of change;

r_{0i} and r_{1i} are the level-2 residuals that represent those portions of the level-2 outcomes that remain unexplained by the level-2 predictors. The level-2 individual variances in *true intercept* and *true slope* across all individuals in the population are represented by σ^2_0 and σ^2_1, respectively, and their covariance represented as σ_{01}.

Figure 6.1. Equation for the impact of service, gender, and interaction over time.

Figure 6.2 visually represents the change in *Community Service* score over time for *Creative Engineering* students, with respect to service and gender (Model E). Model E predicts that females and males in an SL section begin with a slightly higher *Community Service* score (β_{01} = 0.22). Female students in non-service PBL sections begin with a slightly lower *Community Service* score than the other groups (β_{02} = -0.15). Service has a slight impact on increased *Community Service* score over non-service PBL sections (β_{11} = 0.04), while females in SL sections decrease more than other subgroups over time (β_{13} = -0.26), likely due to a ceiling effect. Overall, this model still reflects that SL section has a bigger impact than gender on where high school students start with regard to attitudes towards community service, while females in non-service PBL sections (who start out lower than females in SL sections) have the greatest gains in score over the semester.

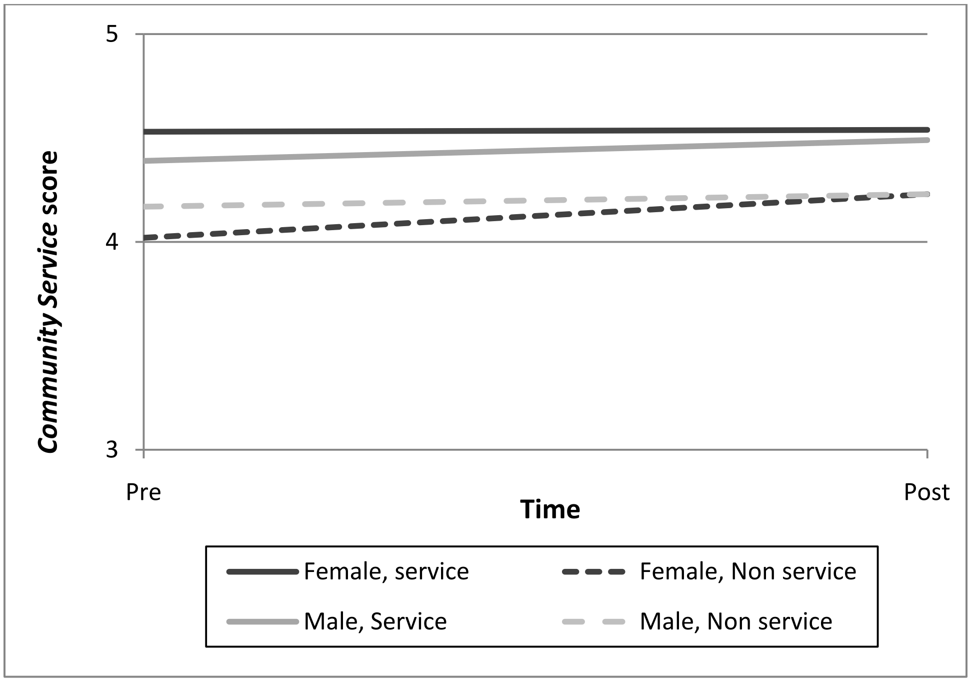

Figure 6.2. Prototypical change trajectories recovered from the HLM analyses for *Community Service* score in 82 high school subjects by service, gender, and their interaction (Model E). Time is reported in test administration. Vertical axis is restricted for sensitivity to scaling issues.

Figure 6.3 visually represents the change in *Community Service* score over time for FYEP students, with respect to service and gender (Model E). This model predicts that females and males in SL sections begin with only a slightly higher *Community Service* score than their peers in non-service PBL sections (β_{01} = 0.2), while all female students begin with a significantly higher *Community Service* score (β_{02} = 0.39). Service and gender have only a slight impact on changing score over time (β_{11} = -0.02, and β_{12} = -0.09), while females in SL sections barely negate the decrease over time (β_{13} = 0.03). The decrease in score is also likely due to a ceiling effect on gender. Overall, this model reflects that gender has a bigger impact on where FYEP students start with regard to attitudes towards community service than service, while neither gender nor service has a practical impact on changing attitudes over one semester.

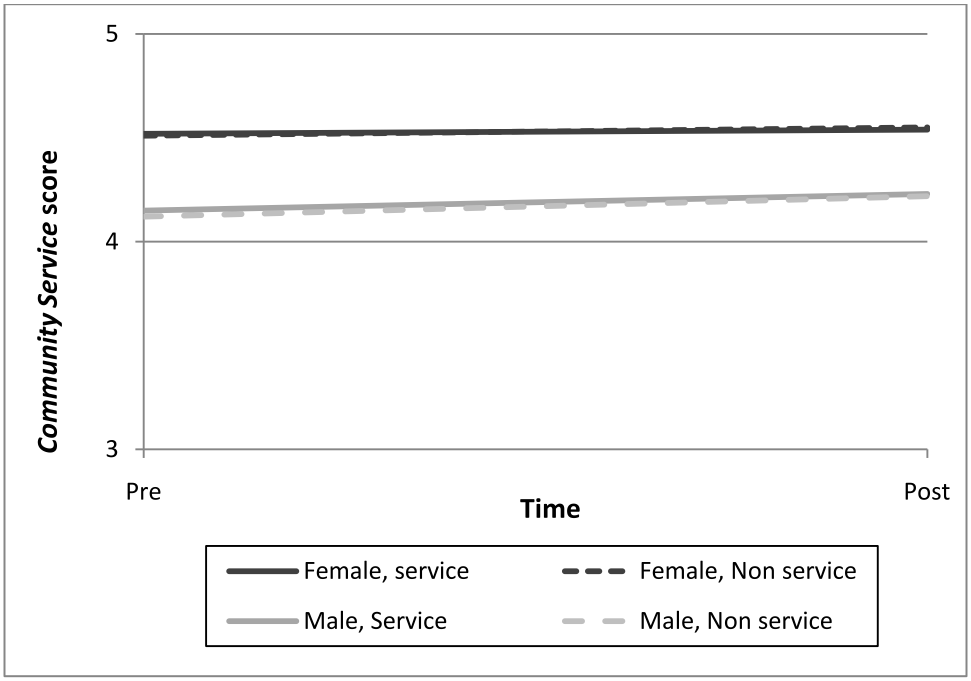

Figure 6.3. Prototypical change trajectories recovered from the HLM analyses for *Community Service* score in 272 FYEP subjects by service, gender, and their interaction (Model E). Time is reported in test administration. Vertical axis is restricted for sensitivity to scaling issues.

Residual analyses and the "ceiling effect"

In order to confirm the patterns in Figures 6.2 and 6.3 and determine if our assumptions are reasonable, we took a closer look at the residuals from Model E in both cohorts of students. Residuals are the calculated differences obtained by subtracting the observed responses from the predicted responses. Residual files were created and analyzed in SPSS.

In the high school cohort, Empirical Bayes estimates for standard deviation of time were highest for the males enrolled in an SL section (SD = 0.53), suggesting that the variability in slopes is greatest for this group. In the FYEP cohort, Empirical Bayes estimates for standard deviation of time were again highest for the males enrolled in an SL section (SD = 0.57), suggesting that the variability in slopes is greatest for this group as well. An examination of the sum of the fitted and residual (EC) correlation was negative for all students, offering a predicted pattern of highest growth greatest for those students with the lowest initial *Community Service* scores.

The graphs of individuals for both cohorts indicate a possible “ceiling effect,” where some students start with a high score on attitudes towards community service and stay there over the semester. To mitigate the impact of the ceiling effect, we also chose to compare residuals from a restricted range of high school students who had initial pre-survey *Community Service* scores between 3.3 and 4.8. This range was selected to remove the highest initial-scoring (*n*=18 with scores >4.8) and lowest initial-scoring students (*n*=13 with scores <3.3) and therefore make the analysis more sensitive to scaling issues. 81% of the students eliminated from the restricted group were males, with only 3 females in the group that had an initial score less than 3.3 (10%). The demographics of the restricted group are in Table 6.7. The correlations for the smaller group of students were lower, indicating that the students in the “middle” (*n*=51) grew differently than the entire group (*N*=82). These students who initially score their *Community Service* attitudes lower increased over time, except for males in service sections who initially score lower decreased over time. In comparing the EC means of the restricted set, the female students in service sections had slightly higher relative slopes than the other subgroups.

Table 6.7. Demographic distributions of high school and first-year students participating in the “restricted set” (number and percent, where appropriate).

K-12 Students	**N**	**%**	**FYEP students**	**N**	**%**
Middle range	**51**		**Middle range**	**168**	
Female	20	39%	Female	38	23%
Male	31	61%	Male	130	77%
Service	14	27%	Service	84	50%
Non-Service	37	73%	Non-Service	84	50%

We also chose to compare residuals from a restricted range of FYEP students who had initial pre-survey *Community Service* scores between 3.6 and 4.8. This range was selected to remove the highest-scoring (*n*=57 with scores >4.8) and lowest-scoring students (*n*=47 with scores <3.6) and therefore make the analysis more sensitive to scaling issues. 71% of the students eliminated from the restricted group were males, with only 5 females in the group that initially scored < 3.6 (5%). The demographics of the restricted group are also in Table 6.7. The correlations for the smaller group of students were lower, indicating that the students in the "middle" (*n*=168) grew differently than the entire group (*N*=272). All FYEP students who initially score their *Community Service* attitudes lower increased over time. In comparing the EC means of the restricted set, the male students in service sections had slightly higher relative slopes than the other subgroups, while the females in service sections had slightly negative mean slopes.

Limitations of the study

It is important to note that there are various limitations to this study which limits the generalizability of the findings. First and foremost, the cohort of participants comes from one semester of enrollment in an engineering design course. Previous research has discussed the limited ability to change attitudes over one semester, and this study supports that reasoning (Bielefeldt et al., 2008; Canney & Bielefeldt, 2012). Courses and experiences outside the two offerings mentioned here also impact student perceptions and attitudes. However, most of the high school students in the Skyline STEM Academy have a similar course load, and first semester students at the University of Colorado Boulder also take very similar courses regardless of major. It would be useful to extend this study to all high school and entering first-year students across semesters to see if the trends continue.

Next, as mentioned earlier, the items from the CSAS survey factored out differently between high school and college. The high school and FYEP attitudes do not represent the exact same questions since the FYEP construct includes three questions related to an awareness of the needs that can be met by engineering that are not present for the high school students. This may indicate a difference in how students perceive community service from high school (approximately 16 years old) to the first year of a college degree (approximately 18 years old). It would be useful to use open-ended questions and interviews to further understand the differences in interpretation of the items between age groups.

Finally, the ceiling effect had a definite impact on the analyses in this paper. Most high school and first-year students scored the items representing attitudes towards community service very high, leaving almost no room for growth in the pre-survey. The good news is that those students maintained their high scores, which was represented by little evidence of predicted decreasing scores over time. In other words, Figures 6.2 and 6.3 do not illustrate decreasing slopes, and the greatest predicted decrease in slope from Tables 6.5 and 6.6 are at a rate of -0.09 points over the entire semester for high school females in service sections and FYEP females in non-service sections.

Discussion

Engineering wants to develop future professionals to understand the ethical and social implications of their work. Ethics, as an important part of ABET criteria and an important part of teaching professionalism, is a requirement for socially responsible citizenship (Fleischmann, 2003). Professional engineers recommend that we engage students in more higher-order activities; students indicate more effective learning when their activities reflect hands-on project based learning; however, this is still not a common thread in many engineering education programs (Goel & Sharda, 2004). In order to develop social and ethical responsibility towards the global community in engineering students, it is imperative to better understand how our students' attitudes towards service to the community develop, and if a predisposition to service impacts how the students learn from their SL experience, at both the K-12 and collegiate levels.

Using an HLM method, we looked for changing patterns in self-reported attitudes towards community service in high school and first-year engineering students over the course of one semester. We also investigated the impact of SL and gender on these attitudes. A closer look at these predicted change trajectories provided interesting patterns in subsets of students, including:

- Service predicted the greatest variability in high school student attitudes towards community service, with students in service sections starting at a higher intercept than their peers in non-service sections. We predict that this is likely due to the ability of these students to choose into which section topic they enrolled before the start of the course.
- Gender predicted the greatest impact on FYEP students' community service attitudes, with females starting at a higher intercept than the males. We predict this reflects a greater sense of responsibility towards community service for females who are starting college.
- There was a "ceiling effect" for both groups of students, indicating that some students maintain a high *Community Service* score pre- to post- semester. This is consistent with previous studies and literature around attitudes towards service of high school and college-aged students (Lopez, 2002; RMC Research Corporation, 2002; Reeb et al., 2010). The good news is that those students maintained their high scores, which was represented little evidence of predicted decreasing scores over time.

- The analyses of a restricted set of students showed that students in the "middle" for both high school and FYEP cohort changed differently over time than the overall group. The main difference was that students who initially score their *Community Service* attitudes lower than their peers increased their score at a greater rate over the semester.

Based on our study results, educators seeking to foster an increased sense of professional responsibility in engineering students should consider engaging students in project-based service-learning experiences. Despite some students choosing to enroll in service-based sections at the high school level or a pre-disposition towards service for females at the first-year college level, all of our study participants maintained a high opinion of community service over the course of the semester. Enrollment in a service-learning section of a projects course did not significantly increase the attitudes towards community service of our students, likely because all of the attitude scores were already very high. In short, this generation of students at both the high school and college levels already has positive attitudes towards service to the community.

Why not use the knowledge that students are favorable towards service to help them learn the technical and professional skills to succeed in life? We need to offer students more practice with real-world problems that do not have a right answer, to meet the expectations of ABET and professional engineers and to better prepare students for the professional realm. Our research supports PBSL as an instructional method to accomplish these goals and to help nurture students' responsibility towards helping others along the way.

CHAPTER VII

CONCLUSIONS AND FUTURE WORK

A review of the current literature provides strong support for hands-on, project-based service-learning (PBSL) engineering design experiences as an instructional method to improve student knowledge and attitudes towards engineering. This thesis examined the evolving identification with engineering and attitudes toward community service for both high school and first-year engineering students engaged in project-based design and whether a service-learning context influences these changing attitudes. Several hypotheses were put forward: PBSL would not differentially impact the identity or community service attitudes of female students, PBSL would have a positive impact on identity with engineering for high school students considered minorities in engineering, and PBSL would have a larger impact on high school students' personal responsibility towards community service than for first-year undergraduate students. Many of these hypotheses proved accurate; however, predicted trends were more evident than highly significant measurable changes in identity or attitudes towards community service over one semester or two semesters of PBSL coursework.

In Chapter IV, the calculated trajectories of first-year engineering students' identity during the first semester of engineering undergraduate study did not differ greatly by gender, reinforcing the findings of the Academic Pathways Study (APS) that suggest engineering identity does not vary considerably by gender (Atman et al., 2010). For this analysis, the greatest impact on the students' changing identity over time was intent to complete a major in engineering. Students in SL sections who start with a lower intent to complete a major in engineering have greater gains in engineering identity over the semester than their peers in non-SL sections. A brief look at retention indicates that students who left engineering were already moving away from identity with the profession as early as their first semester; with the undergraduate students who were not retained in non-service sections decreasing in identity score even more that the students in service sections that were not retained.

In Chapter V, with regard to high school students and their developing identity with engineering, there was an increase in identity with engineering as a result of exposure to PBSL across gender and ethnicities. Females in service sections out-gained females in non-service sections and students considered minorities in engineering in service sections outgained all other students over the year. All sub-populations of students studied have the same predicted pattern of high growth for initially lower identity scores. This supports PBL as an instructional method to increase students' identity with engineering, with or without a service context. Overall, the greatest decreases in identity score were for female students not engaged in any service section over the course of the year.

In Chapter VI, with regard to attitudes towards community service in high school and first-year undergraduate students, enrollment in a PBSL section predicted the greatest variability in high school student attitudes, with students in service sections starting at a higher intercept than their peers in non-service sections. This is likely due to the ability of these students to choose into which section topic they enroll before the start of the course. On the other hand, gender predicted the greatest impact on FYEP students' community service attitudes, with females starting with a higher score on their pre-survey than the males. This likely reflects a greater sense of responsibility towards the community service for females who are starting college. Enrollment in a service-learning section of a projects course did not significantly increase the attitudes towards community service of our students, likely because all of the attitude scores were already very high.

In most analyses, a "ceiling effect" was observed where some students start with the highest score on self-perceptions of identity and community service and stayed there throughout the year. This was especially prevalent in the attitudes towards community service scores pre- to post- semester. This is consistent with previous studies and literature around attitudes towards service of high school and college-aged students (Lopez, 2002; RMC Research Corporation, 2002; Reeb et al., 2010). The good news is that those students maintained their high scores, and there was little evidence of decreasing scores over time. In short, this generation of students at both the high school and college levels already has positive attitudes towards service to the community.

This study indicates that PBSL projects can help students develop a meaningful identity with engineering and maintain a high level of societal and ethical responsibility towards service in the community, in order to meet the expectations of ABET and practicing engineers and to better prepare students for the professional workforce. The opportunity to engage in engineering experiences that are relevant, specifically using a SL context, has the potential to impact many facets of students' growth along their academic careers, including interest and recruitment of women and minority students into the pipeline of engineering education and the engineering workforce. Based on the results of this study, K-12 and undergraduate institutions seeking to increase diverse students' identification with engineering should consider PBSL engineering design experiences early and often.

This research is just a starting point. The survey data collected includes additional factors not considered in the scope of this work. The current analyses support further investigation into identity and community service attitudes of pre-college and undergraduate engineering students. Some follow-on ideas for future investigations include:

- Extend this study across multiple cohorts and years to all entering first-year college and STEM Academy students to see if the trends continue. The expanded data set will be useful to substantiate the patterns found in this initial study.
- Query first year-students at a variety of time intervals after their first semester of an engineering undergraduate degree to help determine any significant and enduring impacts of early participation in service experiences on identity, similar to those found for undergraduate students in liberal arts and education majors (Batchelder & Root, 1994; S. R. Jones & Abes, 2004).
- Follow this cohort of STEM Academy students after four possible years in the program to see if the patterns in identity and attitudes towards community service persist and even more Academy graduates move into engineering undergraduate programs
- Look deeply into retention of first-year engineering students. Our preliminary exploration suggested that students who left engineering were already moving away from identity with the profession as early as their first semester. This was also differentiated by participation in a service section, with the participants not retained in non-SL sections displaying the lowest scores on identity with engineering. While the number of participants was small, the impact of identity and service on retention could have very profound implications for engineering education.
- The quantitative survey items analyses in this study were coupled with open-ended questions for the FYEP participants, and open-ended questions along with semi-structured focus groups for participants in the high school course. It would be useful to

examine the individual answers to open-ended questions and interviews to further understand the differences in interpretation of the items between age groups.

- Other constructs measured in the high school survey, but not included in this study include composite measures of self-reported efficacy and interest in engineering, awareness of the needs that can be met by engineering contributions, and confidence in engineering-related skills (math, science, problem solving) (See Appendix F). Preliminary statistical analysis was performed on self-reported efficacy and awareness for students in the fall 2010 sections of Creative Engineering Design — and results suggested that the students in the service section out-gained their peers in efficacy and awareness — a deeper dive into whether these patterns persist across grades and sub-groups of students in high school would be a valuable contribution to the advancement of pre-college engineering education (Zarske et al., 2012). Any relationship between self-confidence in engineering-related skills and retention of these students into college-engineering careers would also be enlightening.
- Other constructs measured in the FYEP survey, but not included in this study include composite measures of self-reported confidence in engineering-related skills, preparedness to incorporate technical skills (manufacturing skills, problem solving, data analysis) while practicing as an engineer, and preparedness to incorporate professional skills (presentation skills, management skills, teamwork) while practicing as an engineer (see Appendix F). While preliminary statistical analysis was performed on both technical and professional skills for the fall 2010 — and concluded that service has a positive impact on those students' perceived skills in both areas — there is more analysis to be

done on how well service courses predict these gains and how self-confidence in engineering skills is related (Zarske, Reamon, et al., 2012).

- Preliminary descriptive statistics on attitudes towards *Community Service* for minority-identifying and majority-identifying high school and FYEP students indicate an increase in attitudes for undergraduate students in SL-sections and a decrease in attitudes for high school students in SL-sections (see Appendix F). While the scope of this thesis did not capture these relationships due to small numbers of participants in the SL minority-identifying population, future work will include expanding the data set to include additional semesters and modeling the relationships between community service attitudes and ethnicity.
- Finally, while this study looked at the impacts of engagement in a semester-long course, it would be interesting to examine the individual components of PBSL instruction, including the community context, teamwork, and reflection, to discern what is working and which sub-populations of students are impacted by each component.

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Appendix A

Principal Components Analysis for First-Year Engineering Projects (FYEP) Survey

Table 1. Total variance explained for first 20 components in 5-factor Principal Components Analysis.

	Initial Eigenvalues			Rotation Sums of Squared Loadings
Component	**Total**	**% of Variance**	**Cumulative %**	**Total**
1	25.481	29.977	29.977	22.727
2	9.874	11.616	41.594	9.946
3	4.085	4.806	46.400	9.380
4	3.789	4.458	50.857	15.765
5	3.202	3.768	54.625	5.620
6	2.121	2.495	57.120	
7	1.691	1.990	59.110	
8	1.659	1.952	61.062	
9	1.401	1.648	62.710	
10	1.340	1.577	64.286	
11	1.277	1.502	65.789	
12	1.155	1.358	67.147	
13	1.111	1.307	68.454	
14	1.067	1.256	69.709	
15	1.030	1.212	70.921	
16	1.016	1.195	72.116	
17	.948	1.115	73.231	
18	.922	1.085	74.316	
19	.853	1.004	75.319	
20	.806	.949	76.268	

Table 2. Scree Plot for 5-factor Principal Components Analysis.

Table 3. Rotated pattern matrix for 5-factor Principal Components Analysis; Oblimin with Kaiser Normalization.

	Component				
	1	2	3	4	5
CONF29	.896				
CONF30	.881				
CONF32	.869				
CONF24	.854				
CONF31	.827				
CONF14	.822				
CONF12	.821				
CONF21	.807				
CONF19	.806				
CONF9	.800				
CONF28	.779				
CONF3	.776				
CONF33	.776				
CONF10	.771				
CONF17	.759				
CONF26	.749				
CONF23	.721				
CONF20	.671				
CONF22	.642			.307	
CONF25	.630			.327	
CONF27	.580			.353	
CONF1	.565				
CONF18	.565				
CONF7	.558				
CONF15	.554			.343	
CONF4	.545				
CONF5	.543				
CONF13	.536			.371	
CONF8	.527				
CONF6	.484				
CONF16	.396			.395	
CS8		.855			
CS13		.828			
CS6		.811			
CS2		.810			
CS11		.795			
CS14		.777			

CS15		.745			
CS5		.737			
CS1		.713			
CS3		.708			
CS12		.687			
CS7		.678			
CS10		.668			
CS9		.647			
CS4		.622			
ID3			.802		
ID2			.800		
ID5			.784		
ID4			.757		
ID11			.733		
ID10			.678		
ID7			.631		
ID1			.567		
ID9			.507		
ID8			.400		
ID6			.329		
SKILL16				.785	
SKILL6				.724	
SKILL1				.664	
SKILL21				.637	
SKILL17				.630	
SKILL24				.630	
SKILL18				.624	
SKILL23				.592	
SKILL8				.575	
SKILL25				.520	
SKILL5				.517	
SKILL15				.514	
SKILL26				.498	
SKILL9				.467	
SKILL14				.452	
SKILL20				.425	
CONF11	.412			.418	
CONF2	.389			.405	
SKILL12					.613
SKILL13					.576
SKILL10					.469
SKILL4					.464
SKILL11					.442

SKILL22					.436
SKILL3					.403
SKILL2					.388
SKILL7				.332	.382
SKILL19					.316

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 21 iterations.

Table 4. Component correlation matrix for 5-factor Principal Components Analysis.

Component	1	2	3	4	5
1	1.000	.031	.332	.500	.198
2	.031	1.000	.186	.181	-.175
3	.332	.186	1.000	.245	.022
4	.500	.181	.245	1.000	.109
5	.198	-.175	.022	.109	1.000

Table 5. Total variance explained for first 20 components in 6-factor Principal Components Analysis.

	Initial Eigenvalues			Rotation Sums of Squared Loadings
Component	Total	% of Variance	Cumulative %	Total
1	25.481	29.977	29.977	22.793
2	9.874	11.616	41.594	9.747
3	4.085	4.806	46.400	10.345
4	3.789	4.458	50.857	15.742
5	3.202	3.768	54.625	4.590
6	2.121	2.495	57.120	3.508
7	1.691	1.990	59.110	
8	1.659	1.952	61.062	
9	1.401	1.648	62.710	
10	1.340	1.577	64.286	
11	1.277	1.502	65.789	
12	1.155	1.358	67.147	
13	1.111	1.307	68.454	
14	1.067	1.256	69.709	
15	1.030	1.212	70.921	
16	1.016	1.195	72.116	
17	.948	1.115	73.231	
18	.922	1.085	74.316	
19	.853	1.004	75.319	
20	.806	.949	76.268	

Table 6. Scree Plot for 6-factor Principal Components Analysis.

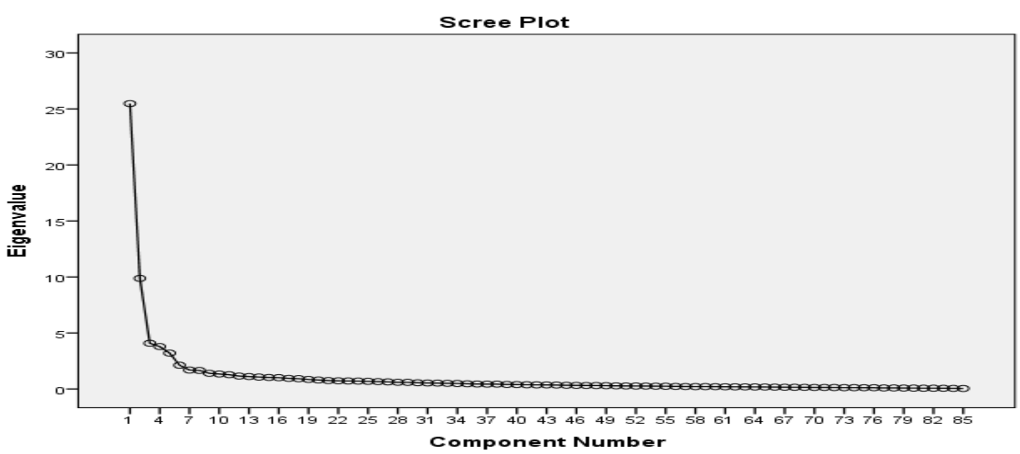

Table 7. Rotated pattern matrix for 6-factor Principal Components Analysis; Oblimin with Kaiser Normalization.

	Component					
	1	2	3	4	5	6
CONF29	.896					
CONF30	.881					
CONF32	.877					
CONF24	.860					
CONF31	.834					
CONF14	.824					
CONF12	.820					
CONF21	.812					
CONF19	.810					
CONF9	.800					
CONF33	.780					
CONF28	.779					
CONF3	.773					
CONF10	.773					
CONF17	.755					
CONF26	.755					
CONF23	.722					
CONF20	.667					
CONF22	.647					
CONF25	.634					
CONF27	.578				-.346	
CONF18	.568					
CONF7	.561					
CONF1	.561					
CONF15	.551				-.343	
CONF5	.547					
CONF4	.545					
CONF13	.534			.323		
CONF8	.527					
CONF6	.485					
CONF11	.408			.364		
CONF2	.394			.393		
CONF16	.387			.321	-.332	
CS8		.867				
CS6		.840				
CS11		.838				
CS2		.828				
CS14		.817				

CS13		.815				
CS5		.779				
CS3		.689				
CS1		.672				
CS15		.661				.381
CS7		.626				
CS4		.600				
CS12		.584				.427
CS9		.530				.525
ID3			.862			
ID2			.854			
ID11			.761			
ID5			.746			
ID4			.700			
ID10			.693			
ID7			.652			
ID1			.595			
ID9			.500			
SKILL16				.770		
SKILL6				.742		
SKILL1				.690		
SKILL21				.653		
SKILL17				.643		
SKILL18				.635		
SKILL23				.595		
SKILL24				.572	-.342	
SKILL8				.570		
SKILL5				.544		
SKILL15				.525		
SKILL25				.496		
SKILL26				.489		
SKILL14				.474		
SKILL20				.460		
SKILL9				.453		
SKILL7				.368	.343	
SKILL12					.548	
SKILL13					.502	
SKILL10					.466	
SKILL22				.310	.445	
SKILL2				.322	.413	
SKILL4					.413	
SKILL11					.363	
SKILL19					.340	

SKILL3					.311	
ID8						.626
ID6						.595
CS10		.536				.568

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 21 iterations.

Table 8. Component correlation matrix for 6-factor Principal Components Analysis.

Component	1	2	3	4	5	6
1	1.000	.045	.382	.505	.129	-.052
2	.045	1.000	.121	.176	-.164	.183
3	.382	.121	1.000	.282	.068	.078
4	.505	.176	.282	1.000	.047	-.021
5	.129	-.164	.068	.047	1.000	-.126
6	-.052	.183	.078	-.021	-.126	1.000

Appendix B

Principal Components Analysis for High School Creative Engineering Survey

Table 1. Total variance explained for first 20 components in 5-factor Principal Components Analysis.

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total
1	13.578	25.619	25.619	9.476
2	5.608	10.582	36.200	8.323
3	3.661	6.908	43.108	6.962
4	2.500	4.717	47.825	6.439
5	2.085	3.934	51.759	3.356
6	1.749	3.299	55.059	
7	1.582	2.986	58.044	
8	1.520	2.868	60.912	
9	1.332	2.513	63.425	
10	1.239	2.337	65.761	
11	1.166	2.199	67.961	
12	1.131	2.133	70.094	
13	1.008	1.902	71.995	
14	.970	1.830	73.825	
15	.883	1.665	75.490	
16	.855	1.613	77.103	
17	.814	1.535	78.638	
18	.755	1.425	80.063	
19	.712	1.343	81.406	
20	.668	1.260	82.666	

Table 2. Scree Plot for 5-factor Principal Components Analysis.

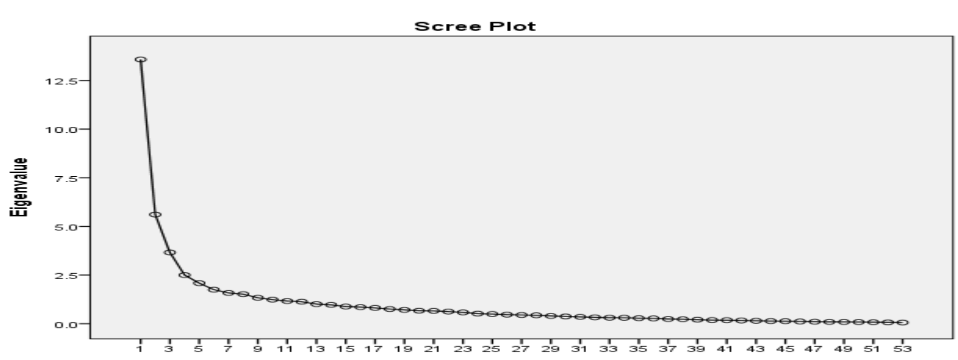

Table 3. Rotated pattern matrix for 5-factor Principal Components Analysis; Oblimin with Kaiser Normalization.

	Component				
	1	2	3	4	5
Id2	.891				
Id11	.869				
Id8	.847				
Id1	.842				
Id3	.816				
Id9	.802				
Id10	.771				
Id7	.749				
Id4	.638				
Eff15	.421	.384			
Int11	.420				
Eff4	.340				.307
CS8		.735			
CS4		.733			
CS7		.712			
CS3		.696		.307	
CS2		.694	-.363		
CS5		.682			
CS6		.679			
CS14		.679			
CS9		.645			
CS15		.615	.353		
CS13		.516	.450		
Eff14		.458	.304		
CS1		.414		.351	
Int10			.676		
Eff6			.660		
Eff7			.569		
Int7	.304		.550		
Int8	.398		.549		
Eff1			.505	.330	
Eff9			.483		
Eff13			.462		
Int12	.399		.445		
Aware1			.336		
Aware4			.268		
CS11				.675	-.352
CS10		.310		.638	-.311

Id6	.307			.632	.310
CS12		.328		.550	
Id5	.437			.534	
Int9			.314	.508	
Aware3				.481	
Aware2				.471	
Aware5				.369	.300
Eff11				.250	
Eff8					.610
Eff2					.505
Eff3					.440
Eff5		.346	.383		.424
Eff12					-.417
Eff10					.377
Aware6					.332

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 14 iterations.

Table 4. Component correlation matrix for 5-factor Principal Components Analysis.

Component	1	2	3	4	5
1	1.000	.133	.233	.230	.126
2	.133	1.000	.221	.302	.052
3	.233	.221	1.000	.188	.170
4	.230	.302	.188	1.000	.090
5	.126	.052	.170	.090	1.000

Table 5. Total variance explained for first 20 components in 6-factor Principal Components Analysis.

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total
1	13.578	25.619	25.619	9.354
2	5.608	10.582	36.200	8.030
3	3.661	6.908	43.108	6.664
4	2.500	4.717	47.825	5.822
5	2.085	3.934	51.759	5.156
6	1.749	3.299	55.059	2.374
7	1.582	2.986	58.044	
8	1.520	2.868	60.912	
9	1.332	2.513	63.425	
10	1.239	2.337	65.761	
11	1.166	2.199	67.961	
12	1.131	2.133	70.094	
13	1.008	1.902	71.995	
14	.970	1.830	73.825	
15	.883	1.665	75.490	
16	.855	1.613	77.103	
17	.814	1.535	78.638	
18	.755	1.425	80.063	
19	.712	1.343	81.406	
20	.668	1.260	82.666	

Table 6. Scree Plot for 6-factor Principal Components Analysis.

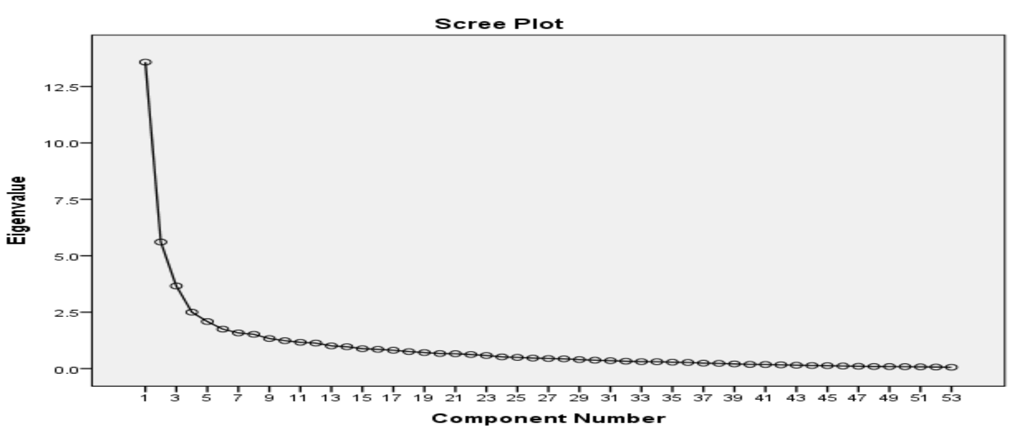

Table 7. Rotated pattern matrix for 6-factor Principal Components Analysis; Oblimin with Kaiser Normalization.

	Component					
	1	2	3	4	5	6
Id2	.913					
Id11	.853					
Id8	.851					
Id1	.849					
Id3	.832					
Id9	.811					
Id10	.781					
Id7	.737					
Id4	.602					
Int11	.383		.312			
CS4		.752				
CS3		.723		.336		
CS8		.702				
CS5		.701				
CS2		.695	-.355			
CS6		.678				
CS7		.675				
CS9		.648				
CS14		.619				
CS15		.561	.335			
Eff14		.453	.333			
CS13		.436	.405			-.371
CS1		.410		.342		
Eff15	.377	.396	.301			
Int10			.663			
Eff6			.635			
Eff7			.573			
Int7			.543			
Int8	.374		.525			
Eff9			.451			
Int12	.358		.449			
Eff1			.429		.334	
Eff13			.428		.319	
Eff12			.328			
Aware4			.277			
CS11				.705		-.325
CS10				.669		
CS12		.332		.601		

Int9			.310	.527		
Id6	.310			.507	.404	
Aware2				.446		
Id5	.438			.441		
Aware3				.406		
Eff11				.255		
Eff2					.747	
Eff3					.711	
Eff4	.385				.596	
Eff8					.580	
Eff5		.318	.360		.375	
Aware5					.363	
Aware6						.633
Aware1			.399			.417
Eff10						.378

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 25 iterations.

Table 8. Component correlation matrix for 6-factor Principal Components Analysis.

Component	**1**	**2**	**3**	**4**	**5**	**6**
1	1.000	.125	.227	.226	.160	.109
2	.125	1.000	.196	.270	.195	-.015
3	.227	.196	1.000	.143	.247	.062
4	.226	.270	.143	1.000	.163	.026
5	.160	.195	.247	.163	1.000	.157
6	.109	-.015	.062	.026	.157	1.000

Appendix C

Extended Data Output for Chapter IV

Residual analyses for FYEP student identity score, SPSS output

Intent to Complete a Major in Engineering on *Identity* Over Time; Full cohort, *N*=272

$$IDY_{ti} = \beta_{00} + \beta_{01}*INT_i + \beta_{10}*TIME_{ti} + \beta_{11}*INT_i*TIME_{ti} + r_{0i} + r_{1i}*TIME_{ti}$$

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
EBINTRCPT1 * INT	272	100.0%	0	0.0%	272	100.0%
EBTIME * INT	272	100.0%	0	0.0%	272	100.0%

Group		EBINTRCPT1	EBTIME
Intent 1	Mean	1.43925	-.06646
	N	1	1
	Std. Deviation	.	.
Intent 2	Mean	-.30965	.20460
	N	2	2
	Std. Deviation	1.155654	.131072
Intent 3	Mean	-.15747	.01304
	N	17	17
	Std. Deviation	.418603	.520591
Intent 4	Mean	.01440	-.01391
	N	101	101
	Std. Deviation	.495506	.577440
Intent 5	Mean	.00266	.00557
	N	151	151
	Std. Deviation	.503849	.574418
Total	Mean	.00000	.00000
	N	272	272
	Std. Deviation	.506337	.567593

Correlations

INT			EBINTRCPT1	EBTIME
Intent 1	EBINTRCPT1	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)		.
		N	1	1
	EBTIME	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)	.	
		N	1	1
Intent 2	EBINTRCPT1	Pearson Correlation	1	-1.000**
		Sig. (2-tailed)		.
		N	2	2
	EBTIME	Pearson Correlation	-1.000**	1
		Sig. (2-tailed)	.	
		N	2	2
Intent 3	EBINTRCPT1	Pearson Correlation	1	-.283
		Sig. (2-tailed)		.272
		N	17	17
	EBTIME	Pearson Correlation	-.283	1
		Sig. (2-tailed)	.272	
		N	17	17
Intent 4	EBINTRCPT1	Pearson Correlation	1	-.146
		Sig. (2-tailed)		.144
		N	101	101
	EBTIME	Pearson Correlation	-.146	1
		Sig. (2-tailed)	.144	
		N	101	101
Intent 5	EBINTRCPT1	Pearson Correlation	1	-.348**
		Sig. (2-tailed)		.000
		N	151	151
	EBTIME	Pearson Correlation	-.348**	1
		Sig. (2-tailed)	.000	
		N	151	151

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

a. Cannot be computed because at least one of the variables is constant.

INT		ECINTRCPT1	ECTIME
Intent 1	Mean	4.26524	.28353
	N	1	1
	Std. Deviation	.	.
Intent 2	Mean	2.82147	.45316
	N	2	2
	Std. Deviation	1.155654	.131072
Intent 3	Mean	3.27877	.16017
	N	17	17
	Std. Deviation	.418603	.520591
Intent 4	Mean	3.75576	.03179
	N	101	101
	Std. Deviation	.495506	.577440
Intent 5	Mean	4.04914	-.05016
	N	151	151
	Std. Deviation	.503849	.574418
Total	Mean	3.88382	-.00165
	N	272	272
	Std. Deviation	.547321	.571781

Correlations

INT			ECINTRCPT1	ECTIME
Intent 1	ECINTRCPT1	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)		.
		N	1	1
	ECTIME	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)	.	
		N	1	1
Intent 2	ECINTRCPT1	Pearson Correlation	1	-1.000**
		Sig. (2-tailed)		.
		N	2	2
	ECTIME	Pearson Correlation	-1.000**	1
		Sig. (2-tailed)	.	
		N	2	2
Intent 3	ECINTRCPT1	Pearson Correlation	1	-.283
		Sig. (2-tailed)		.272
		N	17	17

	ECTIME	Pearson Correlation	-.283	1
		Sig. (2-tailed)	.272	
		N	17	17
Intent 4	ECINTRCPT1	Pearson Correlation	1	-.146
		Sig. (2-tailed)		.144
		N	101	101
	ECTIME	Pearson Correlation	-.146	1
		Sig. (2-tailed)	.144	
		N	101	101
Intent 5	ECINTRCPT1	Pearson Correlation	1	-.348**
		Sig. (2-tailed)		.000
		N	151	151
	ECTIME	Pearson Correlation	-.348**	1
		Sig. (2-tailed)	.000	
		N	151	151

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

a. Cannot be computed because at least one of the variables is constant.

Intent to Complete a Major in Engineering on *Identity* Over Time; *n*=149

Restricted range = 3<ECINTERCEPT<4

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
ECINTRCPT1 * INT	149	100.0%	0	0.0%	149	100.0%
ECTIME * INT	149	100.0%	0	0.0%	149	100.0%

INT		ECINTRCPT1	ECTIME
Intent 2	Mean	3.63864	.36048
	N	1	1
	Std. Deviation	.	.
Intent 3	Mean	3.39338	.10680
	N	12	12
	Std. Deviation	.255733	.489977
Intent 4	Mean	3.60056	.09091
	N	68	68

	Std. Deviation	.279955	.594923
Intent 5	Mean	3.63320	.11723
	N	68	68
	Std. Deviation	.272044	.563929
Total	Mean	3.59902	.10601
	N	149	149
	Std. Deviation	.278966	.568012

Correlations

INT			ECINTRCPT1	ECTIME
Intent 2	ECINTRCPT1	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)		.
		N	1	1
	ECTIME	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)	.	
		N	1	1
Intent 3	ECINTRCPT1	Pearson Correlation	1	-.163
		Sig. (2-tailed)		.613
		N	12	12
	ECTIME	Pearson Correlation	-.163	1
		Sig. (2-tailed)	.613	
		N	12	12
Intent 4	ECINTRCPT1	Pearson Correlation	1	-.079
		Sig. (2-tailed)		.523
		N	68	68
	ECTIME	Pearson Correlation	-.079	1
		Sig. (2-tailed)	.523	
		N	68	68
Intent 5	ECINTRCPT1	Pearson Correlation	1	-.300*
		Sig. (2-tailed)		.013
		N	68	68
	ECTIME	Pearson Correlation	-.300*	1
		Sig. (2-tailed)	.013	
		N	68	68

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

a. Cannot be computed because at least one of the variables is constant.

Service, *Intent*, and Interaction on *Identity* Over Time; Full cohort, *N*=272

$$IDY_{ij} = \beta_{00} + \beta_{02}*SERV_i + \beta_{05}*INT_i + \beta_{091}*SERV\_INT_i + \beta_{10}*TIME_{ti} + \beta_{12}*SERV_i*TIME_{ti} + \beta_{15}*INT_i*TIME_{ti} + \beta_{119}*SERV\_INT_i*TIME_{ti} + r_{0i} + r_{1i}*TIME_{ti}$$

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
EBINTRCPT1 * group	272	100.0%	0	0.0%	272	100.0%
EBTIME * group	272	100.0%	0	0.0%	272	100.0%

group		EBINTRCPT1	EBTIME
Service, intent 2	Mean	-1.01898	.07746
	N	1	1
	Std. Deviation	.	.
Service, intent 3	Mean	-.14155	.02051
	N	8	8
	Std. Deviation	.359426	.537037
Service, intent 4	Mean	.11826	-.01245
	N	45	45
	Std. Deviation	.417415	.643570
Service, intent 5	Mean	-.03730	.00375
	N	85	85
	Std. Deviation	.514564	.517472
No Service, intent 1	Mean	1.32118	.16748
	N	1	1
	Std. Deviation	.	.
No Service, intent 2	Mean	.42366	.27999
	N	1	1
	Std. Deviation	.	.
No Service, intent 3	Mean	-.16248	-.01338
	N	9	9
	Std. Deviation	.482324	.500050
No Service, intent 4	Mean	-.06484	-.02266
	N	56	56
	Std. Deviation	.545630	.519791
No Service, intent 5	Mean	.05074	.01427

	N	66	66
	Std. Deviation	.492025	.642397
Total	Mean	.00000	.00000
	N	272	272
	Std. Deviation	.505676	.565255

Correlations

group			EBINTRCPT1	EBTIME
Service, intent 2	EBINTRCPT1	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)		.
		N	1	1
	EBTIME	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)	.	
		N	1	1
Service, intent 3	EBINTRCPT1	Pearson Correlation	1	-.127
		Sig. (2-tailed)		.764
		N	8	8
	EBTIME	Pearson Correlation	-.127	1
		Sig. (2-tailed)	.764	
		N	8	8
Service, intent 4	EBINTRCPT1	Pearson Correlation	1	-.117
		Sig. (2-tailed)		.442
		N	45	45
	EBTIME	Pearson Correlation	-.117	1
		Sig. (2-tailed)	.442	
		N	45	45
Service, intent 5	EBINTRCPT1	Pearson Correlation	1	-.316**
		Sig. (2-tailed)		.003
		N	85	85
	EBTIME	Pearson Correlation	-.316**	1
		Sig. (2-tailed)	.003	
		N	85	85
No Service, intent 1	EBINTRCPT1	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)		.
		N	1	1
	EBTIME	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)	.	
		N	1	1
No Service, intent 2	EBINTRCPT1	Pearson Correlation	.[a]	.[a]

		Sig. (2-tailed)		.
		N	1	1
	EBTIME	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)	.	
		N	1	1
No Service, intent 3	EBINTRCPT1	Pearson Correlation	1	-.365
		Sig. (2-tailed)		.335
		N	9	9
	EBTIME	Pearson Correlation	-.365	1
		Sig. (2-tailed)	.335	
		N	9	9
No Service, intent 4	EBINTRCPT1	Pearson Correlation	1	-.202
		Sig. (2-tailed)		.135
		N	56	56
	EBTIME	Pearson Correlation	-.202	1
		Sig. (2-tailed)	.135	
		N	56	56
No Service, intent 5	EBINTRCPT1	Pearson Correlation	1	-.398**
		Sig. (2-tailed)		.001
		N	66	66
	EBTIME	Pearson Correlation	-.398**	1
		Sig. (2-tailed)	.001	
		N	66	66

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

a. Cannot be computed because at least one of the variables is constant.

group		ECINTRCPT1	ECTIME
Service, intent 2	Mean	2.00345	.54730
	N	1	1
	Std. Deviation	.	.
Service, intent 3	Mean	3.22800	.30582
	N	8	8
	Std. Deviation	.359426	.537037
Service, intent 4	Mean	3.83492	.08833
	N	45	45
	Std. Deviation	.417415	.643570
Service, intent 5	Mean	4.02648	-.07999
	N	85	85

	Std. Deviation	.514564	.517472
No Service, intent 1	Mean	4.26616	.28197
	N	1	1
	Std. Deviation	.	.
No Service, intent 2	Mean	3.63930	.35934
	N	1	1
	Std. Deviation	.	.
No Service, intent 3	Mean	3.32382	.03083
	N	9	9
	Std. Deviation	.482324	.500050
No Service, intent 4	Mean	3.69212	-.01359
	N	56	56
	Std. Deviation	.545630	.519791
No Service, intent 5	Mean	4.07836	-.01179
	N	66	66
	Std. Deviation	.492025	.642397
Total	Mean	3.88382	-.00165
	N	272	272
	Std. Deviation	.547321	.571781

Correlations

group			ECINTRCPT1	ECTIME
Service, intent 2	ECINTRCPT1	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)		.
		N	1	1
	ECTIME	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)	.	
		N	1	1
Service, intent 3	ECINTRCPT1	Pearson Correlation	1	-.127
		Sig. (2-tailed)		.764
		N	8	8
	ECTIME	Pearson Correlation	-.127	1
		Sig. (2-tailed)	.764	
		N	8	8
Service, intent 4	ECINTRCPT1	Pearson Correlation	1	-.117
		Sig. (2-tailed)		.442
		N	45	45
	ECTIME	Pearson Correlation	-.117	1
		Sig. (2-tailed)	.442	

		N	45	45
Service, intent 5	ECINTRCPT1	Pearson Correlation	1	-.316**
		Sig. (2-tailed)		.003
		N	85	85
	ECTIME	Pearson Correlation	-.316**	1
		Sig. (2-tailed)	.003	
		N	85	85
No Service, intent 1	ECINTRCPT1	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)		.
		N	1	1
	ECTIME	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)	.	
		N	1	1
No Service, intent 2	ECINTRCPT1	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)		.
		N	1	1
	ECTIME	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)	.	
		N	1	1
No Service, intent 3	ECINTRCPT1	Pearson Correlation	1	-.365
		Sig. (2-tailed)		.335
		N	9	9
	ECTIME	Pearson Correlation	-.365	1
		Sig. (2-tailed)	.335	
		N	9	9
No Service, intent 4	ECINTRCPT1	Pearson Correlation	1	-.202
		Sig. (2-tailed)		.135
		N	56	56
	ECTIME	Pearson Correlation	-.202	1
		Sig. (2-tailed)	.135	
		N	56	56
No Service, intent 5	ECINTRCPT1	Pearson Correlation	1	-.398**
		Sig. (2-tailed)		.001
		N	66	66
	ECTIME	Pearson Correlation	-.398**	1
		Sig. (2-tailed)	.001	
		N	66	66

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

a. Cannot be computed because at least one of the variables is constant.

Service, *Intent*, and Interaction on *Identity* Over Time; *n*=150

Restricted range = 3<ECINTERCEPT<4

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
ECINTRCPT1 * group	150	100.0%	0	0.0%	150	100.0%
ECTIME * group	150	100.0%	0	0.0%	150	100.0%

group		ECINTRCPT1	ECTIME
Service, intent 3	Mean	3.34844	.30153
	N	6	6
	Std. Deviation	.332366	.580721
Service, intent 4	Mean	3.65392	.12174
	N	30	30
	Std. Deviation	.242583	.681908
Service, intent 5	Mean	3.61577	.05795
	N	40	40
	Std. Deviation	.293190	.526970
No Service, intent 2	Mean	3.63930	.35934
	N	1	1
	Std. Deviation	.	.
No Service, intent 3	Mean	3.43818	-.08769
	N	6	6
	Std. Deviation	.169334	.317400
No Service, intent 4	Mean	3.55840	.06660
	N	38	38
	Std. Deviation	.302707	.524438
No Service, intent 5	Mean	3.66994	.19176
	N	29	29
	Std. Deviation	.245578	.604084
Total	Mean	3.60170	.10469
	N	150	150
	Std. Deviation	.279938	.566335

Correlations

group			ECINTRCPT1	ECTIME
Service, intent 3	ECINTRCPT1	Pearson Correlation	1	-.128
		Sig. (2-tailed)		.809
		N	6	6
	ECTIME	Pearson Correlation	-.128	1
		Sig. (2-tailed)	.809	
		N	6	6
Service, intent 4	ECINTRCPT1	Pearson Correlation	1	.075
		Sig. (2-tailed)		.695
		N	30	30
	ECTIME	Pearson Correlation	.075	1
		Sig. (2-tailed)	.695	
		N	30	30
Service, intent 5	ECINTRCPT1	Pearson Correlation	1	-.269
		Sig. (2-tailed)		.093
		N	40	40
	ECTIME	Pearson Correlation	-.269	1
		Sig. (2-tailed)	.093	
		N	40	40
No Service, intent 2	ECINTRCPT1	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)		.
		N	1	1
	ECTIME	Pearson Correlation	.[a]	.[a]
		Sig. (2-tailed)	.	
		N	1	1
No Service, intent 3	ECINTRCPT1	Pearson Correlation	1	.009
		Sig. (2-tailed)		.986
		N	6	6
	ECTIME	Pearson Correlation	.009	1
		Sig. (2-tailed)	.986	
		N	6	6
No Service, intent 4	ECINTRCPT1	Pearson Correlation	1	-.225
		Sig. (2-tailed)		.173
		N	38	38
	ECTIME	Pearson Correlation	-.225	1
		Sig. (2-tailed)	.173	
		N	38	38
No Service, intent 5	ECINTRCPT1	Pearson Correlation	1	-.399*

		Sig. (2-tailed)		.032
		N	29	29
		Pearson Correlation	-.399*	1
	ECTIME	Sig. (2-tailed)	.032	
		N	29	29

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

a. Cannot be computed because at least one of the variables is constant.

Appendix D

Extended Data Output for Chapter V

Residual analyses for high school student identity score, SPSS output

Service, gender, and interaction on *Identity* Over Time; Restricted cohort, *n*=81

Restricted range = Identity $\leq$ 4.5

$$IDENTITY_{ti} = \beta_{00} + \beta_{01}*GEND_i + \beta_{10}*TIME\_1_{ti} + \beta_{11}*GEND_i*TIME\_1_{ti} + \beta_{20}*TIME\_2_{ti} + \beta_{21}*GEND_i*TIME\_2_{ti} + \beta_{30}*TIME\_3_{ti} + \beta_{31}*GEND_i*TIME\_3_{ti} + r_{0i} + r_{1i}*TIME\_1_{ti} + r_{2i}*TIME\_2_{ti} + r_{3i}*TIME\_3_{ti}$$

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
EBINTRCPT1 * group	81	100.0%	0	0.0%	81	100.0%
EBTIME_1 * group	81	100.0%	0	0.0%	81	100.0%
EBTIME_2 * group	81	100.0%	0	0.0%	81	100.0%
EBTIME_3 * group	81	100.0%	0	0.0%	81	100.0%

group		EBINTRCPT1	EBTIME_1	EBTIME_2	EBTIME_3
Service 1st, Female	Mean	.00000	.00000	.00000	.00000
	N	8	8	8	8
	Std. Deviation	.568525	.469541	.418396	.609204
Service 2nd, Female	Mean	.00000	.00000	.00000	.00000
	N	10	10	10	10
	Std. Deviation	.467668	.556487	.477777	.537402
No Service , Female	Mean	.00000	.00000	-.00001	.00000
	N	7	7	7	7
	Std. Deviation	.646755	.661045	.513321	.866846
Service 1st, Male	Mean	.00000	.00000	.00000	.00000
	N	17	17	17	17
	Std. Deviation	.518487	.801620	.718014	.930371
Service 2nd, Male	Mean	.00000	.00000	-.00001	.00000
	N	27	27	27	27
	Std. Deviation	.635751	.613498	.726610	.983158

No Service , Male	Mean	.00000	.00000	.00000	.00000
	N	12	12	12	12
	Std. Deviation	.614037	.406105	.504092	.504094
Total	Mean	.00000	.00000	.00000	.00000
	N	81	81	81	81
	Std. Deviation	.566768	.600352	.608602	.802199

Correlations

group			EBINTRCPT1	EBTIME_1	EBTIME_2	EBTIME_3
Service 1st, Female	EBINTRCPT1	Pearson Correlation	1	-.737*	-.690	-.776*
		Sig. (2-tailed)		.037	.058	.024
		N	8	8	8	8
	EBTIME_1	Pearson Correlation	-.737*	1	.980**	.937**
		Sig. (2-tailed)	.037		.000	.001
		N	8	8	8	8
	EBTIME_2	Pearson Correlation	-.690	.980**	1	.975**
		Sig. (2-tailed)	.058	.000		.000
		N	8	8	8	8
	EBTIME_3	Pearson Correlation	-.776*	.937**	.975**	1
		Sig. (2-tailed)	.024	.001	.000	
		N	8	8	8	8
Service 2nd, Female	EBINTRCPT1	Pearson Correlation	1	-.524	-.536	-.611
		Sig. (2-tailed)		.120	.111	.060
		N	10	10	10	10
	EBTIME_1	Pearson Correlation	-.524	1	.624	.309
		Sig. (2-tailed)	.120		.054	.386
		N	10	10	10	10
	EBTIME_2	Pearson Correlation	-.536	.624	1	.445
		Sig. (2-tailed)	.111	.054		.198
		N	10	10	10	10
	EBTIME_3	Pearson Correlation	-.611	.309	.445	1
		Sig. (2-tailed)	.060	.386	.198	
		N	10	10	10	10
No Service , Female	EBINTRCPT1	Pearson Correlation	1	-.710	-.515	-.748
		Sig. (2-tailed)		.074	.237	.053
		N	7	7	7	7
	EBTIME_1	Pearson Correlation	-.710	1	.856*	.958**
		Sig. (2-tailed)	.074		.014	.001

		N	7	7	7	7
	EBTIME_2	Pearson Correlation	-.515	.856*	1	.837*
		Sig. (2-tailed)	.237	.014		.019
		N	7	7	7	7
	EBTIME_3	Pearson Correlation	-.748	.958**	.837*	1
		Sig. (2-tailed)	.053	.001	.019	
		N	7	7	7	7
Service 1st, Male	EBINTRCPT1	Pearson Correlation	1	-.576*	-.538*	-.668**
		Sig. (2-tailed)		.015	.026	.003
		N	17	17	17	17
	EBTIME_1	Pearson Correlation	-.576*	1	.990**	.982**
		Sig. (2-tailed)	.015		.000	.000
		N	17	17	17	17
	EBTIME_2	Pearson Correlation	-.538*	.990**	1	.961**
		Sig. (2-tailed)	.026	.000		.000
		N	17	17	17	17
	EBTIME_3	Pearson Correlation	-.668**	.982**	.961**	1
		Sig. (2-tailed)	.003	.000	.000	
		N	17	17	17	17
Service 2nd, Male	EBINTRCPT1	Pearson Correlation	1	-.483*	-.337	-.443*
		Sig. (2-tailed)		.011	.086	.021
		N	27	27	27	27
	EBTIME_1	Pearson Correlation	-.483*	1	.906**	.874**
		Sig. (2-tailed)	.011		.000	.000
		N	27	27	27	27
	EBTIME_2	Pearson Correlation	-.337	.906**	1	.932**
		Sig. (2-tailed)	.086	.000		.000
		N	27	27	27	27
	EBTIME_3	Pearson Correlation	-.443*	.874**	.932**	1
		Sig. (2-tailed)	.021	.000	.000	
		N	27	27	27	27
No Service , Male	EBINTRCPT1	Pearson Correlation	1	-.067	-.296	-.675*
		Sig. (2-tailed)		.835	.350	.016
		N	12	12	12	12
	EBTIME_1	Pearson Correlation	-.067	1	.800**	.680*
		Sig. (2-tailed)	.835		.002	.015
		N	12	12	12	12
	EBTIME_2	Pearson Correlation	-.296	.800**	1	.839**
		Sig. (2-tailed)	.350	.002		.001

		N	12	12	12	12
	EBTIME_3	Pearson Correlation	-.675*	.680*	.839**	1
		Sig. (2-tailed)	.016	.015	.001	
		N	12	12	12	12

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

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

group		ECINTRCPT1	ECTIME_1	ECTIME_2	ECTIME_3
Service 1st, Female	Mean	3.79167	.42708	.30358	.38777
	N	8	8	8	8
	Std. Deviation	.568525	.469541	.418396	.609204
Service 2nd, Female	Mean	3.93333	-.08258	-.05705	.00833
	N	10	10	10	10
	Std. Deviation	.467668	.556487	.477777	.537402
No Service , Female	Mean	3.76143	.13143	-.19397	-.27585
	N	7	7	7	7
	Std. Deviation	.646755	.661045	.513321	.866846
Service 1st, Male	Mean	3.77941	.54545	.56406	.69182
	N	17	17	17	17
	Std. Deviation	.518487	.801620	.718014	.930371
Service 2nd, Male	Mean	3.70988	.25954	.10958	.08609
	N	27	27	27	27
	Std. Deviation	.635751	.613498	.726610	.983158
No Service , Male	Mean	3.71023	.16730	.45303	.72643
	N	12	12	12	12
	Std. Deviation	.614037	.406105	.504092	.504094
Total	Mean	3.76464	.26912	.22820	.29700
	N	81	81	81	81
	Std. Deviation	.571279	.630754	.658052	.871365

Correlations

group			ECINTRCPT1	ECTIME_1	ECTIME_2	ECTIME_3
Service 1st, Female	ECINTRCPT1	Pearson Correlation	1	-.737*	-.690	-.776*
		Sig. (2-tailed)		.037	.058	.024
		N	8	8	8	8
	ECTIME_1	Pearson Correlation	-.737*	1	.980**	.937**
		Sig. (2-tailed)	.037		.000	.001
		N	8	8	8	8

	ECTIME_2	Pearson Correlation	-.690	.980**	1	.975**
		Sig. (2-tailed)	.058	.000		.000
		N	8	8	8	8
	ECTIME_3	Pearson Correlation	-.776*	.937**	.975**	1
		Sig. (2-tailed)	.024	.001	.000	
		N	8	8	8	8
Service 2nd, Female	ECINTRCPT1	Pearson Correlation	1	-.524	-.536	-.611
		Sig. (2-tailed)		.120	.111	.060
		N	10	10	10	10
	ECTIME_1	Pearson Correlation	-.524	1	.624	.309
		Sig. (2-tailed)	.120		.054	.386
		N	10	10	10	10
	ECTIME_2	Pearson Correlation	-.536	.624	1	.445
		Sig. (2-tailed)	.111	.054		.198
		N	10	10	10	10
	ECTIME_3	Pearson Correlation	-.611	.309	.445	1
		Sig. (2-tailed)	.060	.386	.198	
		N	10	10	10	10
No Service , Female	ECINTRCPT1	Pearson Correlation	1	-.710	-.515	-.748
		Sig. (2-tailed)		.074	.237	.053
		N	7	7	7	7
	ECTIME_1	Pearson Correlation	-.710	1	.856*	.958**
		Sig. (2-tailed)	.074		.014	.001
		N	7	7	7	7
	ECTIME_2	Pearson Correlation	-.515	.856*	1	.837*
		Sig. (2-tailed)	.237	.014		.019
		N	7	7	7	7
	ECTIME_3	Pearson Correlation	-.748	.958**	.837*	1
		Sig. (2-tailed)	.053	.001	.019	
		N	7	7	7	7
Service 1st, Male	ECINTRCPT1	Pearson Correlation	1	-.576*	-.538*	-.668**
		Sig. (2-tailed)		.015	.026	.003
		N	17	17	17	17
	ECTIME_1	Pearson Correlation	-.576*	1	.990**	.982**
		Sig. (2-tailed)	.015		.000	.000
		N	17	17	17	17
	ECTIME_2	Pearson Correlation	-.538*	.990**	1	.961**
		Sig. (2-tailed)	.026	.000		.000
		N	17	17	17	17

	ECTIME_3	Pearson Correlation	-.668**	.982**	.961**	1
		Sig. (2-tailed)	.003	.000	.000	
		N	17	17	17	17
Service 2nd, Male	ECINTRCPT1	Pearson Correlation	1	-.483*	-.337	-.443*
		Sig. (2-tailed)		.011	.086	.021
		N	27	27	27	27
	ECTIME_1	Pearson Correlation	-.483*	1	.906**	.874**
		Sig. (2-tailed)	.011		.000	.000
		N	27	27	27	27
	ECTIME_2	Pearson Correlation	-.337	.906**	1	.932**
		Sig. (2-tailed)	.086	.000		.000
		N	27	27	27	27
	ECTIME_3	Pearson Correlation	-.443*	.874**	.932**	1
		Sig. (2-tailed)	.021	.000	.000	
		N	27	27	27	27
No Service , Male	ECINTRCPT1	Pearson Correlation	1	-.067	-.296	-.675*
		Sig. (2-tailed)		.835	.350	.016
		N	12	12	12	12
	ECTIME_1	Pearson Correlation	-.067	1	.800**	.680*
		Sig. (2-tailed)	.835		.002	.015
		N	12	12	12	12
	ECTIME_2	Pearson Correlation	-.296	.800**	1	.839**
		Sig. (2-tailed)	.350	.002		.001
		N	12	12	12	12
	ECTIME_3	Pearson Correlation	-.675*	.680*	.839**	1
		Sig. (2-tailed)	.016	.015	.001	
		N	12	12	12	12

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

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

Service, ethnicity, and interaction on *Identity* Over Time; Restricted cohort, *n*=81

Restricted range = Identity ≤ 4.5

$IDENTITY_{ti} = \beta_{00} + \beta_{01}*URM_i + \beta_{10}*TIME\_1_{ti} + \beta_{11}*URM_i*TIME\_1_{ti} + \beta_{20}*TIME\_2_{ti} + \beta_{21}*URM_i*TIME\_2_{ti} + \beta_{30}*TIME\_3_{ti} + \beta_{31}*URM_i*TIME\_3_{ti} + r_{0i} + r_{1i}*TIME\_1_{ti} + r_{2i}*TIME\_2_{ti} + r_{3i}*TIME\_3_{ti}$

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
EBINTRCPT1 * group	81	100.0%	0	0.0%	81	100.0%
EBTIME_1 * group	81	100.0%	0	0.0%	81	100.0%
EBTIME_2 * group	81	100.0%	0	0.0%	81	100.0%
EBTIME_3 * group	81	100.0%	0	0.0%	81	100.0%

group		EBINTRCPT1	EBTIME_1	EBTIME_2	EBTIME_3
Service 1st, URM	Mean	.00000	.00000	.00000	.00000
	N	12	12	12	12
	Std. Deviation	.628682	.881598	.821580	1.094950
Service 2nd, URM	Mean	.00000	.00000	-.00001	.00000
	N	11	11	11	11
	Std. Deviation	.351101	.542460	.328706	.392136
No Service , URM	Mean	.00000	.00000	.00000	.00001
	N	11	11	11	11
	Std. Deviation	.666197	.530448	.663750	.852547
Service 1st, Majority	Mean	.00000	.00000	.00000	.00000
	N	13	13	13	13
	Std. Deviation	.416875	.526245	.488033	.602526
Service 2nd, Majority	Mean	.00000	.00000	.00000	.00000
	N	26	26	26	26
	Std. Deviation	.622454	.621951	.774040	1.032586
No Service , Majority	Mean	.00000	.00000	.00000	.00000
	N	8	8	8	8
	Std. Deviation	.557140	.411963	.288628	.535879
Total	Mean	.00000	.00000	.00000	.00000
	N	81	81	81	81
	Std. Deviation	.547301	.596736	.625807	.829281

Correlations

group			EBINTRCPT1	EBTIME_1	EBTIME_2	EBTIME_3
Service 1st, URM	EBINTRCPT1	Pearson Correlation	1	-.670*	-.652*	-.752**
		Sig. (2-tailed)		.017	.022	.005
		N	12	12	12	12
	EBTIME_1	Pearson Correlation	-.670*	1	.985**	.966**
		Sig. (2-tailed)	.017		.000	.000
		N	12	12	12	12
	EBTIME_2	Pearson Correlation	-.652*	.985**	1	.958**
		Sig. (2-tailed)	.022	.000		.000
		N	12	12	12	12
	EBTIME_3	Pearson Correlation	-.752**	.966**	.958**	1
		Sig. (2-tailed)	.005	.000	.000	
		N	12	12	12	12
Service 2nd, URM	EBINTRCPT1	Pearson Correlation	1	-.168	.073	-.044
		Sig. (2-tailed)		.621	.831	.899
		N	11	11	11	11
	EBTIME_1	Pearson Correlation	-.168	1	.871**	.184
		Sig. (2-tailed)	.621		.000	.588
		N	11	11	11	11
	EBTIME_2	Pearson Correlation	.073	.871**	1	.527
		Sig. (2-tailed)	.831	.000		.096
		N	11	11	11	11
	EBTIME_3	Pearson Correlation	-.044	.184	.527	1
		Sig. (2-tailed)	.899	.588	.096	
		N	11	11	11	11
No Service , URM	EBINTRCPT1	Pearson Correlation	1	-.539	-.708*	-.773**
		Sig. (2-tailed)		.087	.015	.005
		N	11	11	11	11
	EBTIME_1	Pearson Correlation	-.539	1	.847**	.780**
		Sig. (2-tailed)	.087		.001	.005
		N	11	11	11	11
	EBTIME_2	Pearson Correlation	-.708*	.847**	1	.963**
		Sig. (2-tailed)	.015	.001		.000
		N	11	11	11	11
	EBTIME_3	Pearson Correlation	-.773**	.780**	.963**	1
		Sig. (2-tailed)	.005	.005	.000	
		N	11	11	11	11

Service 1st, Majority	EBINTRCPT1	Pearson Correlation	1	-.408	-.439	-.611*
		Sig. (2-tailed)		.166	.133	.026
		N	13	13	13	13
	EBTIME_1	Pearson Correlation	-.408	1	.999**	.972**
		Sig. (2-tailed)	.166		.000	.000
		N	13	13	13	13
	EBTIME_2	Pearson Correlation	-.439	.999**	1	.980**
		Sig. (2-tailed)	.133	.000		.000
		N	13	13	13	13
	EBTIME_3	Pearson Correlation	-.611*	.972**	.980**	1
		Sig. (2-tailed)	.026	.000	.000	
		N	13	13	13	13
Service 2nd, Majority	EBINTRCPT1	Pearson Correlation	1	-.529**	-.438*	-.530**
		Sig. (2-tailed)		.005	.025	.005
		N	26	26	26	26
	EBTIME_1	Pearson Correlation	-.529**	1	.890**	.890**
		Sig. (2-tailed)	.005		.000	.000
		N	26	26	26	26
	EBTIME_2	Pearson Correlation	-.438*	.890**	1	.905**
		Sig. (2-tailed)	.025	.000		.000
		N	26	26	26	26
	EBTIME_3	Pearson Correlation	-.530**	.890**	.905**	1
		Sig. (2-tailed)	.005	.000	.000	
		N	26	26	26	26
No Service , Majority	EBINTRCPT1	Pearson Correlation	1	-.164	.348	-.534
		Sig. (2-tailed)		.697	.399	.173
		N	8	8	8	8
	EBTIME_1	Pearson Correlation	-.164	1	.525	.603
		Sig. (2-tailed)	.697		.182	.114
		N	8	8	8	8
	EBTIME_2	Pearson Correlation	.348	.525	1	.403
		Sig. (2-tailed)	.399	.182		.322
		N	8	8	8	8
	EBTIME_3	Pearson Correlation	-.534	.603	.403	1
		Sig. (2-tailed)	.173	.114	.322	
		N	8	8	8	8

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

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

group		ECINTRCPT1	ECTIME_1	ECTIME_2	ECTIME_3
Service 1st, URM	Mean	3.70833	.54167	.53640	.68148
	N	12	12	12	12
	Std. Deviation	.628682	.881598	.821580	1.094950
Service 2nd, URM	Mean	4.12121	-.06061	.02451	.03030
	N	11	11	11	11
	Std. Deviation	.351101	.542460	.328706	.392136
No Service , URM	Mean	3.68358	.02372	.33766	.28665
	N	11	11	11	11
	Std. Deviation	.666197	.530448	.663750	.852547
Service 1st, Majority	Mean	3.85256	.47611	.48092	.54447
	N	13	13	13	13
	Std. Deviation	.416875	.526245	.488033	.602526
Service 2nd, Majority	Mean	3.62179	.26340	.08743	.07118
	N	26	26	26	26
	Std. Deviation	.622454	.621951	.774040	1.032586
No Service , Majority	Mean	3.79167	.33333	.19699	.47645
	N	8	8	8	8
	Std. Deviation	.557140	.411963	.288628	.535879
Total	Mean	3.76464	.26912	.25336	.30129
	N	81	81	81	81
	Std. Deviation	.571279	.630754	.655370	.865680

Correlations

group			ECINTRCPT1	ECTIME_1	ECTIME_2	ECTIME_3
Service 1st, URM	ECINTRCPT1	Pearson Correlation	1	-.670*	-.652*	-.752**
		Sig. (2-tailed)		.017	.022	.005
		N	12	12	12	12
	ECTIME_1	Pearson Correlation	-.670*	1	.985**	.966**
		Sig. (2-tailed)	.017		.000	.000
		N	12	12	12	12
	ECTIME_2	Pearson Correlation	-.652*	.985**	1	.958**
		Sig. (2-tailed)	.022	.000		.000
		N	12	12	12	12
	ECTIME_3	Pearson Correlation	-.752**	.966**	.958**	1
		Sig. (2-tailed)	.005	.000	.000	
		N	12	12	12	12

Service 2nd, URM	ECINTRCPT1	Pearson Correlation	1	-.168	.073	-.044
		Sig. (2-tailed)		.621	.831	.899
		N	11	11	11	11
	ECTIME_1	Pearson Correlation	-.168	1	.871**	.184
		Sig. (2-tailed)	.621		.000	.588
		N	11	11	11	11
	ECTIME_2	Pearson Correlation	.073	.871**	1	.527
		Sig. (2-tailed)	.831	.000		.096
		N	11	11	11	11
	ECTIME_3	Pearson Correlation	-.044	.184	.527	1
		Sig. (2-tailed)	.899	.588	.096	
		N	11	11	11	11
No Service , URM	ECINTRCPT1	Pearson Correlation	1	-.539	-.708*	-.773**
		Sig. (2-tailed)		.087	.015	.005
		N	11	11	11	11
	ECTIME_1	Pearson Correlation	-.539	1	.847**	.780**
		Sig. (2-tailed)	.087		.001	.005
		N	11	11	11	11
	ECTIME_2	Pearson Correlation	-.708*	.847**	1	.963**
		Sig. (2-tailed)	.015	.001		.000
		N	11	11	11	11
	ECTIME_3	Pearson Correlation	-.773**	.780**	.963**	1
		Sig. (2-tailed)	.005	.005	.000	
		N	11	11	11	11
Service 1st, Majority	ECINTRCPT1	Pearson Correlation	1	-.408	-.439	-.611*
		Sig. (2-tailed)		.166	.133	.026
		N	13	13	13	13
	ECTIME_1	Pearson Correlation	-.408	1	.999**	.972**
		Sig. (2-tailed)	.166		.000	.000
		N	13	13	13	13
	ECTIME_2	Pearson Correlation	-.439	.999**	1	.980**
		Sig. (2-tailed)	.133	.000		.000
		N	13	13	13	13
	ECTIME_3	Pearson Correlation	-.611*	.972**	.980**	1
		Sig. (2-tailed)	.026	.000	.000	
		N	13	13	13	13
Service 2nd, Majority	ECINTRCPT1	Pearson Correlation	1	-.529**	-.438*	-.530**
		Sig. (2-tailed)		.005	.025	.005
		N	26	26	26	26
	ECTIME_1	Pearson Correlation	-.529**	1	.890**	.890**

		Sig. (2-tailed)	.005		.000	.000
		N	26	26	26	26
	ECTIME_2	Pearson Correlation	-.438*	.890**	1	.905**
		Sig. (2-tailed)	.025	.000		.000
		N	26	26	26	26
	ECTIME_3	Pearson Correlation	-.530**	.890**	.905**	1
		Sig. (2-tailed)	.005	.000	.000	
		N	26	26	26	26
No Service , Majority	ECINTRCPT1	Pearson Correlation	1	-.164	.348	-.534
		Sig. (2-tailed)		.697	.399	.173
		N	8	8	8	8
	ECTIME_1	Pearson Correlation	-.164	1	.525	.603
		Sig. (2-tailed)	.697		.182	.114
		N	8	8	8	8
	ECTIME_2	Pearson Correlation	.348	.525	1	.403
		Sig. (2-tailed)	.399	.182		.322
		N	8	8	8	8
	ECTIME_3	Pearson Correlation	-.534	.603	.403	1
		Sig. (2-tailed)	.173	.114	.322	
		N	8	8	8	8

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

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

Appendix E

Extended Data Output for Chapter V

Residual analyses for high school student *Community Service* (CS) score, SPSS output

Service, gender, and interaction on *Community Service* Over Time; Full cohort, *N*=82

$$CS_{ti} = \beta_{00} + \beta_{01}*GEND_i + \beta_{02}*SERV_i + \beta_{03}*GEND\_SRV_i + \beta_{10}*TIME_{ti} + \beta_{11}*GEND_i*TIME_{ti} + \beta_{12}*SERV_i*TIME_{ti} + \beta_{13}*GEND\_SRV_i*TIME_{ti} + r_{0i} + r_{1i}*TIME_{ti}$$

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
EBINTRCPT1 * group	82	100.0%	0	0.0%	82	100.0%
EBTIME * group	82	100.0%	0	0.0%	82	100.0%

group		EBINTRCPT1	EBTIME
Service, Male	Mean	.00000	.00000
	N	14	14
	Std. Deviation	.883626	.529783
Service, Female	Mean	.00000	.00000
	N	9	9
	Std. Deviation	.436351	.384610
No Service, Male	Mean	.00000	.00000
	N	42	42
	Std. Deviation	.701177	.335730
No Service, Female	Mean	.00000	.00000
	N	17	17
	Std. Deviation	.824578	.460025
Total	Mean	.00000	.00000
	N	82	82
	Std. Deviation	.726143	.398135

Correlations

group			EBINTRCPT1	EBTIME
Service, Male	EBINTRCPT1	Pearson Correlation	1	-.829**
		Sig. (2-tailed)		.000
		N	14	14
	EBTIME	Pearson Correlation	-.829**	1
		Sig. (2-tailed)	.000	
		N	14	14
Service, Female	EBINTRCPT1	Pearson Correlation	1	-.872**
		Sig. (2-tailed)		.002
		N	9	9
	EBTIME	Pearson Correlation	-.872**	1
		Sig. (2-tailed)	.002	
		N	9	9
No Service, Male	EBINTRCPT1	Pearson Correlation	1	-.563**
		Sig. (2-tailed)		.000
		N	42	42
	EBTIME	Pearson Correlation	-.563**	1
		Sig. (2-tailed)	.000	
		N	42	42
No Service, Female	EBINTRCPT1	Pearson Correlation	1	-.941**
		Sig. (2-tailed)		.000
		N	17	17
	EBTIME	Pearson Correlation	-.941**	1
		Sig. (2-tailed)	.000	
		N	17	17

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

group		ECINTRCPT1	ECTIME
Service, Male	Mean	4.38690	.09615
	N	14	14
	Std. Deviation	.883626	.529783
Service, Female	Mean	4.52991	.00855
	N	9	9
	Std. Deviation	.436351	.384610
No Service, Male	Mean	4.17150	.05728
	N	42	42

	Std. Deviation	.701177	.335730
No Service, Female	Mean	4.02262	.22851
	N	17	17
	Std. Deviation	.824578	.460025
Total	Mean	4.21675	.09406
	N	82	82
	Std. Deviation	.743072	.404746

Correlations

group			ECINTRCPT1	ECTIME
Service, Male	ECINTRCPT1	Pearson Correlation	1	-.829**
		Sig. (2-tailed)		.000
		N	14	14
	ECTIME	Pearson Correlation	-.829**	1
		Sig. (2-tailed)	.000	
		N	14	14
Service, Female	ECINTRCPT1	Pearson Correlation	1	-.872**
		Sig. (2-tailed)		.002
		N	9	9
	ECTIME	Pearson Correlation	-.872**	1
		Sig. (2-tailed)	.002	
		N	9	9
No Service, Male	ECINTRCPT1	Pearson Correlation	1	-.563**
		Sig. (2-tailed)		.000
		N	42	42
	ECTIME	Pearson Correlation	-.563**	1
		Sig. (2-tailed)	.000	
		N	42	42
No Service, Female	ECINTRCPT1	Pearson Correlation	1	-.941**
		Sig. (2-tailed)		.000
		N	17	17
	ECTIME	Pearson Correlation	-.941**	1
		Sig. (2-tailed)	.000	
		N	17	17

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

Service, gender, and interaction on *Community Service* Over Time; *n*=51

Restricted range = 3.3 <ECINTERCEPT< 4.8

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
ECINTRCPT1 * group	51	100.0%	0	0.0%	51	100.0%
ECTIME * group	51	100.0%	0	0.0%	51	100.0%

group		ECINTRCPT1	ECTIME
Service, Male	Mean	4.25461	.10154
	N	8	8
	Std. Deviation	.485648	.218778
Service, Female	Mean	4.26028	.21535
	N	6	6
	Std. Deviation	.202166	.155142
No Service, Male	Mean	4.17900	.03131
	N	23	23
	Std. Deviation	.415776	.306853
No Service, Female	Mean	4.34256	.05721
	N	14	14
	Std. Deviation	.443727	.262193
Total	Mean	4.24532	.07109
	N	51	51
	Std. Deviation	.411185	.268028

Correlations

group			ECINTRCPT1	ECTIME
Service, Male	ECINTRCPT1	Pearson Correlation	1	.091
		Sig. (2-tailed)		.829
		N	8	8
	ECTIME	Pearson Correlation	.091	1
		Sig. (2-tailed)	.829	
		N	8	8
Service, Female	ECINTRCPT1	Pearson Correlation	1	-.719
		Sig. (2-tailed)		.107

		N	6	6
	ECTIME	Pearson Correlation	-.719	1
		Sig. (2-tailed)	.107	
		N	6	6
No Service, Male	ECINTRCPT1	Pearson Correlation	1	-.209
		Sig. (2-tailed)		.338
		N	23	23
	ECTIME	Pearson Correlation	-.209	1
		Sig. (2-tailed)	.338	
		N	23	23
No Service, Female	ECINTRCPT1	Pearson Correlation	1	-.784**
		Sig. (2-tailed)		.001
		N	14	14
	ECTIME	Pearson Correlation	-.784**	1
		Sig. (2-tailed)	.001	
		N	14	14

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

Residual analyses for FYEP student *Community Service* (CS) score, SPSS output

Service, gender, and interaction on *Community Service* Over Time; Full cohort, *N*=272

$$CS_{ti} = \beta_{00} + \beta_{01}*GEND_i + \beta_{02}*SERV_i + \beta_{03}*GEND\_SRV_i + \beta_{10}*TIME_{ti} + \beta_{11}*GEND_i*TIME_{ti} + \beta_{12}*SERV_i*TIME_{ti} + \beta_{13}*GEND\_SRV_i*TIME_{ti} + r_{0i} + r_{1i}*TIME_{ti}$$

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
EBINTRCPT1 * group	272	100.0%	0	0.0%	272	100.0%
EBTIME * group	272	100.0%	0	0.0%	272	100.0%

group		EBINTRCPT1	EBTIME
Service, Male	Mean	.00000	.00000
	N	106	106
	Std. Deviation	.626964	.566343
Service, Female	Mean	.00000	.00000
	N	33	33
	Std. Deviation	.509595	.396600
No Service, Male	Mean	.00000	.00000
	N	98	98
	Std. Deviation	.625410	.500422
No Service, Female	Mean	.00000	.00000
	N	35	35
	Std. Deviation	.626956	.351541
Total	Mean	.00000	.00000
	N	272	272
	Std. Deviation	.610150	.497982

Correlations

group			EBINTRCPT1	EBTIME
Service, Male	EBINTRCPT1	Pearson Correlation	1	-.289**
		Sig. (2-tailed)		.003
		N	106	106
	EBTIME	Pearson Correlation	-.289**	1
		Sig. (2-tailed)	.003	
		N	106	106

Service, Female	EBINTRCPT1	Pearson Correlation	1	-.368*
		Sig. (2-tailed)		.035
		N	33	33
	EBTIME	Pearson Correlation	-.368*	1
		Sig. (2-tailed)	.035	
		N	33	33
No Service, Male	EBINTRCPT1	Pearson Correlation	1	-.388**
		Sig. (2-tailed)		.000
		N	98	98
	EBTIME	Pearson Correlation	-.388**	1
		Sig. (2-tailed)	.000	
		N	98	98
No Service, Female	EBINTRCPT1	Pearson Correlation	1	-.370*
		Sig. (2-tailed)		.028
		N	35	35
	EBTIME	Pearson Correlation	-.370*	1
		Sig. (2-tailed)	.028	
		N	35	35

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

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

group		ECINTRCPT1	ECTIME
Service, Male	Mean	4.15425	.08170
	N	106	106
	Std. Deviation	.626964	.566343
Service, Female	Mean	4.52697	.02424
	N	33	33
	Std. Deviation	.509595	.396600
No Service, Male	Mean	4.12031	.10255
	N	98	98
	Std. Deviation	.625410	.500422
No Service, Female	Mean	4.51257	.01629
	N	35	35
	Std. Deviation	.626956	.351541
Total	Mean	4.23335	.07382
	N	272	272
	Std. Deviation	.632391	.499034

Correlations

group			ECINTRCPT1	ECTIME
Service, Male	ECINTRCPT1	Pearson Correlation	1	-.289**
		Sig. (2-tailed)		.003
		N	106	106
	ECTIME	Pearson Correlation	-.289**	1
		Sig. (2-tailed)	.003	
		N	106	106
Service, Female	ECINTRCPT1	Pearson Correlation	1	-.368*
		Sig. (2-tailed)		.035
		N	33	33
	ECTIME	Pearson Correlation	-.368*	1
		Sig. (2-tailed)	.035	
		N	33	33
No Service, Male	ECINTRCPT1	Pearson Correlation	1	-.388**
		Sig. (2-tailed)		.000
		N	98	98
	ECTIME	Pearson Correlation	-.388**	1
		Sig. (2-tailed)	.000	
		N	98	98
No Service, Female	ECINTRCPT1	Pearson Correlation	1	-.370*
		Sig. (2-tailed)		.028
		N	35	35
	ECTIME	Pearson Correlation	-.370*	1
		Sig. (2-tailed)	.028	
		N	35	35

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

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

Service, gender, and interaction on *Community Service* Over Time; *n*=168

Restricted range = 3.6 <ECINTERCEPT< 4.8

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
ECINTRCPT1 * group	168	100.0%	0	0.0%	168	100.0%
ECTIME * group	168	100.0%	0	0.0%	168	100.0%

group		ECINTRCPT1	ECTIME
Service, Male	Mean	4.32098	.05484
	N	66	66
	Std. Deviation	.326209	.527435
Service, Female	Mean	4.36682	-.01533
	N	18	18
	Std. Deviation	.325878	.497616
No Service, Male	Mean	4.16240	.04872
	N	64	64
	Std. Deviation	.348550	.497807
No Service, Female	Mean	4.49659	.03534
	N	20	20
	Std. Deviation	.359988	.380754
Total	Mean	4.28639	.04267
	N	168	168
	Std. Deviation	.353773	.493867

Correlations

group			ECINTRCPT1	ECTIME
Service, Male	ECINTRCPT1	Pearson Correlation	1	-.424**
		Sig. (2-tailed)		.000
		N	66	66
	ECTIME	Pearson Correlation	-.424**	1
		Sig. (2-tailed)	.000	
		N	66	66
Service, Female	ECINTRCPT1	Pearson Correlation	1	-.286
		Sig. (2-tailed)		.250
		N	18	18
	ECTIME	Pearson Correlation	-.286	1
		Sig. (2-tailed)	.250	
		N	18	18
No Service, Male	ECINTRCPT1	Pearson Correlation	1	-.319*
		Sig. (2-tailed)		.010
		N	64	64
	ECTIME	Pearson Correlation	-.319*	1
		Sig. (2-tailed)	.010	
		N	64	64
No Service, Female	ECINTRCPT1	Pearson Correlation	1	-.141
		Sig. (2-tailed)		.553
		N	20	20
	ECTIME	Pearson Correlation	-.141	1
		Sig. (2-tailed)	.553	
		N	20	20

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

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

Appendix F

Additional Variables Not Considered in the Thesis

(Ideas for Future Work)

Additional High School Variables

Table 1. Descriptive Statistics for Additional Dependent Variables from the 5-factor Principal Components Analysis for the High School Survey.

Variable	# survey items	*N* Time 0	*N* Time 4	Min	Max	Time 0 Mean (SD)	Time 1 Mean (SD)	Time 2 Mean (SD)	Time 3 Mean (SD)	Mean Difference Within Groups from Time 0 to Time 4 (for 54 students)
Engineering Efficacy	11	102	54	2.10	5.00	4.19 (0.54)	4.29 (0.57)	4.29 (0.57)	4.35 (0.59)	0.06
Awareness of Engineering Contributions to Society	10	102	54	2.80	5.00	4.56 (0.41)	4.54 (0.46)	4.57 (0.52)	4.63 (0.40)	0.03
Engineering-Related Skills	7	102	54	2.20	5.00	4.44 (0.49)	4.34 (0.60)	4.43 (0.57)	4.40 (0.52)	-0.14*

* $p<0.05$

Table 2. Descriptive Statistics for Independent Variables Collected in the High School Survey.

Variable		N	%
Gender	Female	71	70%
	Male	31	30%
Ethnicity	Hispanic	32	31%
	Black	4	4%
	Multi-racial	5	5%
	Asian	11	11%
	White	50	49%
Grade	10th	80	78%
	11th	19	19%
	12th	3	3%

Additional First Year Engineering Variables

Table 3. Descriptive Statistics for Additional Dependent Variables from the 5-factor Principal Components Analysis for the FYEP Survey.

Variable	# survey items	*N*	Min	Max	Pre Survey Mean (SD)	Post Survey Mean (SD)	Mean Difference
Knowledge of Engineering	1	272	1.00	4.00	2.53 (0.62)	2.96 (0.54)	0.43***
Certainty of Engineering as a Career	1	272	1.00	6.00	3.70 (1.21)	3.61 (1.23)	-0.09
Technical Skills Preparation	10	272	1.00	5.00	3.16 (0.72)	3.63 (0.60)	0.47***
Professional Skills Preparation	16	272	1.00	5.00	3.62 (0.59)	3.79 (0.59)	0.17***
Confidence	33	272	1.82	11.00	7.33 (1.70)	8.45 (1.37)	1.12***

***p<0.001

Table 4. Descriptive Statistics for Additional Independent Variables Collected in the FYEP Survey.

Variable		N	%
Gender	Female	68	25%
	Male	204	75%
Ethnicity	Hispanic	22	8%
	Black	5	2%
	Native American	6	2%
	Multi-racial	5	2%
	Asian	15	6%
	White	216	79%
Academic Standing	Freshmen	252	93%
	Sophomore	13	5%
	Junior	4	1%
	Senior	3	1%
U.S Citizen	Yes	261	96%
	No	11	4%
English is First Language	Yes	249	92%
	No	23	8%

Variable		N	%
First Generation College Student	Yes	42	15%
	No	229	84%
Income	High	21	8%
	Upper-Middle	125	46%
	Middle	82	30%
	Lower-Middle	29	11%
	Low	9	3%

Table 5. Descriptive statistics for *Community Service* in high school and FYEP students, by students typically underrepresented in engineering (URM), majority-identifying students (Majority), and service.

	N	Pre Survey Mean (SD)	Post Survey Mean (SD)	Mean Difference
High School Creative Engineering				
Overall	**82**	**4.31 (0.52)**	**4.40 (0.57)**	**0.09***
URM-All	30	4.42 (0.43)	4.44 (0.42)	0.02
Majority- All	52	4.25 (0.57)	4.39 (0.64)	0.14*
Service- URM	9	4.61 (0.25)	4.53 (0.43)	-0.08
No Service - URM	21	4.33 (0.47)	4.40 (0.42)	0.06
Service-Majority	14	4.43 (0.51)	4.59 (0.60)	0.16
No Service -Majority	38	4.18 (0.58)	4.31 (0.64)	0.13*
First-Year Engineering Projects				
Overall	**272**	**4.23 (0.63)**	**4.30 (0.66)**	**0.07***
URM-All	38	4.23 (0.39)	4.37 (0.36)	0.14
Majority- All	234	4.23 (0.62)	4.30 (0.65)	0.07~
Service- URM	19	4.33 (0.65)	4.49 (0.71)	0.16
No Service - URM	19	4.14 (0.80)	4.25 (0.72)	0.11
Service-Majority	117	4.24 (0.62)	4.28 (0.68)	0.04
No Service -Majority	117	4.33 (0.65)	4.49 (0.71)	0.16~

~p <0.10; * p <0.05