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Systems Thinking in Engineering Design: Differences in Expert vs. Novice and Relationship to Personality Traits

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SYSTEMS THINKING IN ENGINEERING DESIGN: DIFFERENCES IN EXPERT VS. NOVICE AND RELATIONSHIP TO PERSONALITY TRAITS

by

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ABSTRACT

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Systems thinking is a hierarchical view of a complex system that can be decomposed into subsystems and smaller components. It is both a cognitive ability and skill that is desired in engineers because of the complex problems that they are expected to solve in the workplace. Developing systems thinking capabilities of the engineering workforce is an industry endeavor as well as a learning outcome for engineering education. This opens opportunities for research to better understand systems thinking of experts (professional engineers) in industry and novices (engineering students) in higher education. The purpose of this study was to understand and compare the differences between expert and novice systems thinking in engineering design. Knowledge of expert and novice systems thinking help inform engineering education on ways to bridge this gap. Additionally, the study explored the relationship between systems thinking and the Big Five personality traits.

Using tools developed from Function-Behavior-Structure (FBS) Ontology, existing protocol data for 61 teams (18 professionals, 19 seniors, and 24 freshmen) underwent systems hierarchical coding. Results from correspondence analysis and hypothesis testing show that systems thinking of senior engineering students are expert-like in some ways and freshmen-like (novice) in other ways. Statistically significant differences were found between expert and novice systems thinking with medium to large effect sizes. Professionals and seniors show higher big-picture or holistic thinking and problem decompose and recompose more than freshmen in their systems thinking process. Consistent with existing literature, freshmen were found to be more focused on the details and were more likely to remain at the details level throughout the design. Professionals distinguished themselves from seniors and freshmen by being more problem-focused in systems thinking, whereas seniors and freshmen were more solution-focused. Contrary to what was hypothesized, members of professional teams interact less than senior and freshman teams when problem decomposing. Additionally, exploratory results from correspondence analysis of a small sample of participants support existing literature that high agreeableness and conscientiousness were common personality traits among systems thinkers. However, there was no correlation between personality traits and systems thinking, therefore, this relationship remains in question and require further investigation. The findings from this study have several implications for engineering education and future research.

(145 pages)

PUBLIC ABSTRACT

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Yuzhen Luo

Systems thinking is the ability to see the big picture and the related elements when designing, and how these relationships form the big picture. In engineering design, systems thinking is valuable to both industry, as well as engineering education. As such, it creates opportunities for researchers to better understand systems thinking of both professional engineers in industry, who are assumed to be the experts, and engineering students in higher education, who are assumed to be the novices. The purpose of this study was to compare and identify the differences between expert and novice systems thinking in engineering design. Additionally, the study explored the relationship between systems thinking and individual personality.

Results from various statistical analysis of 61 teams (18 professionals, 19 seniors, and 24 freshmen) show that professionals are different from senior and freshman students because they focus more on the problem during their systems thinking process, whereas students tend to focus on the solution. Surprisingly, members of professional teams interact less with each other than student teams during the process of breaking down complex problems into smaller and manageable subproblems. The results also showed that there were similarities in systems thinking between professionals and senior students. Additionally, exploratory results from a small subset of the participants show no clear

evidence for a relationship between systems thinking and personality traits. Therefore, the existence of the relationship between systems thinking and personality traits remains in question and require further investigation. The findings from this study have several implications for engineering education and future research.

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CHAPTER I

INTRODUCTION

Engineering systems design is a complex process (Elmaraghy et al., 2012), and modern engineered products have thousands of parts and require hundreds of manufacturing steps to be produced. The drivers of complexity go beyond engineering the product itself and the manufacturing process, but also intertwine and interact with the economical, technological, and social aspects. The engineered product itself is a hierarchy of systems, and within that system there are subsystems. Furthermore, the engineered product interacts with the economical, technological, and societal aspects to form additional systems. Building on this definition, Rouse (2003) defined a system in the most general sense as a group or combination of interrelated, interdependent, or interacting elements that form a collective entity. The engineering of these systems is not foreign to the integrative discipline of systems engineering. It is integrative because it crosses boundaries of other disciplines in engineering and seeks to explore, understand, and design to bring everything together. The success of this lie in the role of systems engineers and their unique thinking abilities.

Successful systems engineers possess a higher order thinking skill – systems thinking (Frank, 2006), which is a form of reasoning that views a complex system as a hierarchy of solution elements (Rouse, 2003). Engineering design utilizes systems thinking to solve complex engineering problems (Behl & Ferreira, 2014), develop complex systems (Honour, 2004), and increase project success (Wasson, 2010). Design refers to the forms of knowledge, that is special to the designer, with the intent to solve ill-structured or “messy” problems (Cross, 2004). During design, systems thinking is

measured through a problem decomposition or top-down and problem recomposition or bottom-up approach to the systems hierarchy (Ho, 2001; Song, 2014). The authors found that experts differed to novices in their problem-solving strategies. Experts primarily used a top-down approach, whereas novices preferred a bottom-up approach.

This study investigates the differences in systems thinking of expert versus novice designers and explores the relationship between personality traits and systems thinking of designers. Statistical analysis such as descriptive statistics, hypotheses testing, correspondence analysis, correlation and analysis of covariance are discussed. The results contribute to our understanding of the gap between expert and novice designers and inform engineering education to bridge the gap.

Problem

Global statistics from 2011 to 2015 attribute project complexity as one of the main reasons for large project failures. This is particularly true for software development (Standish Group, 2015; Whitney & Daniels, 2013). They found that 56% of complex software projects failed, only 2% were successful, and the remaining 42% being challenged (Standish Group, 2015). Project failure was determined by projects not being on time, exceeding budgets, and unsatisfied customers. Moreover, in pursuit of renewable and sustainable energy, larger wind turbines in Europe (Sweden, Finland, and Germany) face increasingly higher rates of failure and shortened lifespan due to lack of engineering design considerations (Ribrant & Bertling, 2007). Bar-yam (2003) asserts that large engineering projects fail because they follow old paradigms to handle complex projects. Instead, complex engineering projects should be managed as an evolutionary process that

undergo continuous rapid improvement. People and new technology should be involved in the design, implementation, and function of complex engineering projects in order to mitigate systems engineering failures (Bar-yam, 2003).

There are many reasons for poor systems engineering, one of them stems from a void in engineering education (Wasson, 2010). Engineers spend 70-80% of their careers solving systems engineering problems, however, they lack the competencies required for systems engineering due to the absence of a formal education at the undergraduate level. Even though universities have established their own systems engineering programs (Ng, 2003), they find it challenging to integrate systems thinking into their engineering curriculum. Engineering design education finds it hard for students to learn design thinking, and harder to teach (Dym, Agogino, Eris, Frey, & Leifer, 2006). Systems thinking and systems design require an engineering education that achieves competence, in addition to specialization in subject knowledge. This requires an ability to learn and progress through an open-ended, formative, and dynamic learning process rather than the traditional 'rote' application of pre-defined knowledge (Godfrey, Crick, & Huang, 2014). ABET (2018) asserted that students should have "an ability to identify, formulate, and solve *complex engineering problems* by applying principles of engineering, science, and mathematics" (pg. 5) as the foremost student outcome for baccalaureate engineering programs in U.S. universities.

As systems become more complex, companies are faced with challenges to develop systems thinking capability of their workforce (Heidi & Martin, 2011). The situation is aggravated as senior practitioners are approaching retirement, creating a need for rapid development of systems engineering expertise to replace the senior systems

engineers (Armstrong & Wade, 2015). Industry has stressed the shortage and need for systems engineers at a local and global level (Gonçalves & Britz, 2009). They believe that candidates for a systems engineering position should possess certain desirable intra- and inter-personal characteristics to have sufficient ‘potential’ to become a competent systems engineer. This expectation is supported by research. Research shows that in addition to work experience and education, successful systems engineers or systems thinkers possess personalities and individual characteristics that enable them to perform systems thinking (Armstrong & Wade, 2015; Behl & Ferreira, 2014; Davidz, 2006; Frank, 2000, 2006; Heidi & Martin, 2011). Majority of these studies used formal and informal interviews to solicit enablers, key factors, and elements to systems thinking of professional engineers from various engineering disciplines. In these studies, participant responses were drawn from their personal experiences and gave descriptions of the characteristics, attitudes, skills, and knowledge that successful systems engineer ought to have. The literature suggests some evidence of a relationship between individual personality and systems thinking, however, it lacks a consistent way to measure the personality of engineers and relating it to systems thinking as a process of actual engineering design. One way to understand the personality of engineers is through personality trait theory, in particular the Big Five.

Personality trait studies stem from the English language, where words can be used to describe one’s personality and behavior (Digman, 1990). These words, or group of words, undergo factor analysis based on their association and are placed into a factor. In the Big Five personality traits, there are five main factors: Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness (Digman, 1990). Openness, is associated

with being a big picture or broad minded or systems thinkers (Roccas, Sagiv, Schwartz, & Knafo, 2002; Davidz, 2006). Similarly, Myers Briggs' Intuition types are also known to be holistic thinkers (McPeek, Martin, & Breiner, 2016). How the trait of *Openness* in the Big Five or how *Intuition* in Myers Briggs relate to systems thinking is still unknown. Both the Big Five and Myers Briggs have strengths and limitations which are discussed in Chapter III - Methodology.

Based on the problem statement, a study to compare expert versus novice designers' systems thinking may help inform engineering education on what and where the gap is. Understanding how experts solve complex problems in engineering design sets a benchmark for future curriculum development. Furthermore, exploring the relationship between personality traits and systems thinking contribute to the body of knowledge in engineering education, where the role of personalities was found to influence systems design and systems thinking. The relationship between personalities and systems thinking are discussed in Chapter II – Review of Literature.

Purpose and Objectives

The purpose of this study was to investigate systems thinking of design teams in engineering. To achieve this, systems thinking of design teams were viewed from an expert versus novice and personality traits point of view. The main objectives were:

1. Compare systems thinking of professional engineers (experts) and engineering students (novices) in engineering design.
2. Explore the relationship between systems thinking and personality traits in engineering design.

Objective 1 compared systems thinking of professional engineers to engineering students when solving problems in engineering design and found significant differences between the two groups. Existing design protocols (61 sessions) were recoded using a systems hierarchy coding scheme (Gero & Mc Neill, 1998; Song, 2014), which formed the data for analysis. There were three research questions associated with objective 1. The first question compared the percentage distributions of systems thinking, which consisted of three system levels (level 1, 2, 3) and two system processes (problem decomposition and problem recomposition) for professional engineers and engineering students. The second question mapped systems thinking onto the Function Behavior Structure (FBS) problem space versus solution space (Jiang, Gero, & Yen, 2014) and compared the problem-solution focus for professional engineers and students. In the context of FBS, designers either try to understand the problem - problem space or find solutions to the problem - solution space. The third question compared the team interactions that occurred during problem decomposition and recomposition. Team interactions were measured by sequential utterances or turn taking between the two-member team. Objective 2 explored the relationship between systems thinking and the Big Five personality traits. It is exploratory due to the small sample size, assumptions, and limitations, which are discussed in the Limitations section. There is one research question associated with objective 2. The research questions and definition of terms are listed in the following section.

The definition of system and systems thinking were derived from the literature review in Chapter II. Definitions of Function-Behavior-Structure (J. S. Gero, 1990; J. S. Gero & Kannengiesser, 2014), systems cognitive effort (Jiang et al., 2014), and team

interactions (J. Gero & Milovanovic, 2019) refer to earlier work accomplished by Dr. Gero and colleagues, which are covered in depth in Chapter III.

Research Questions

This study was guided by the following research questions and hypotheses:

1. What are the differences in systems thinking between professional engineers and engineering students when solving engineering design problems?

    H1: Professional engineers will use problem decomposition and recomposition more than engineering students.

2. What are the differences in systems cognitive effort between professional engineers and engineering students related to FBS problem space and solution space?

    H2: Professional engineers will have more systems level 1 in the "FBS Issues" problem space than engineering students.

    H3: Professional engineers will have more problem decomposition in the "FBS Processes" problem space than engineering students.

3. How do team member interactions affect problem decomposition and recomposition?

    H4: Professional engineers will use problem decomposition more as team interactions increase compared to engineering students.

4. What is the relationship between the Big Five personality traits and systems thinking in engineering design?

Definition of Terms

- *Professional engineers*: engineers that have at least 10 years of industry work experience.
- *Engineering students*: consist of two groups of undergraduate engineering students, freshmen and senior students.
- *System*: the interaction of multiple entities to achieve some higher order function.
- *Systems Thinking*: a hierarchical view of a complex system that can be decomposed into subsystems and smaller component that represent different levels of the system hierarchy. There are three levels:
    - *Level 1*: system as a whole at the top level.
    - *Level 2*: subsystems and their interactions at the middle level.
    - *Level 3*: details of the subsystems at the bottom level.
    - *Problem Decomposition*: a top-down approach by breaking a complex system into sub-systems. In systems level processes, it is going from level: 1→2, 1→3, 2→3.
    - *Problem Recomposition*: a bottom-up approach by assembling the details and subsystems to form the higher-level system. In systems level processes, it is going from level: 2→1, 3→1, 3→2.
- *Function-Behavior-Structure (FBS)*: a tool used to model and measure design in terms of three ontological variables: function, behavior, and structure.

- *Systems Cognitive Effort:* A measure of design teams' systems thinking in the problem space and solution space using tools developed from FBS.
- *Team Interaction:* This occurs when utterances alternate between members of the team. For example, person A's utterance is followed by person B's utterance and vice versa.
- *Big Five Factor*: a tool in personality trait studies that assess the five factors (Extraversion, Openness, Agreeableness, Conscientiousness, Neuroticism) of an individual on a scale of 0 – 100.

Research Method

The research method used for this study was quantitative because research questions 1-3 tested hypotheses and research question 4 explored the relationships between personality traits and systems thinking. In accordance with Johnson and Christensen (2017), such research questions merited a quantitative approach.

The Function-Behavior-Structure (FBS) Ontology (Kan & Gero, 2017) and levels of the problem (J. S. Gero & Mc Neill, 1998) guided the coding for systems thinking. The coding process is referred to as systems coding for conciseness. FBS codes that were previously developed in an NSF funded project (Becker et al., 2019) served as the basis for systems coding. The codes from FBS were obtained through verbal protocol studies, where teams of engineers and students were video recorded while designing a window opening device. The recordings were then transcribed, segmented, coded, and arbitrated to produce the final FBS codes.

An online Big Five Inventory (BFI) personality survey (Soto & John, 2009) was emailed to participants that requested them to self-evaluate to a set of 44 questions. The Big Five is well validated across instruments and observers (McCrae & Costa, 1987) and proven to be consistent in longitudinal studies (Soldz & Vaillant, 1999). The survey questions were distributed to the participants via Utah State University (USU) Qualtrics and took approximately 5-10 minutes to complete. $10 Amazon gift cards were offered as an incentive for voluntary participation. Results from the survey were used to compute the individual and team BFI personality trait scores. Personality trait scores were computed using an algorithm developed by Soto & John (2009). Individual trait scores were averaged to produce trait scores for each team. Although, team averaging has limitations, it is a common method used in team personality research (Barrick, Neubert, Mount, & Stewart, 1998; Mohammed & Angell, 2003; Reilly, Lynn, & Aronson, 2002; C. A. Toh & Miller, 2016).

Hypotheses were tested using descriptive statistics and analysis of variance between professional engineers and engineering students. Significance was considered at $\alpha = 0.05$ level or $p \leq 0.05$. Statistical Package for the Social Sciences (SPSS) was the statistical software used for the analysis. For research question 4, relationships between personality traits and systems thinking were explored by correspondence analysis, correlation, and analysis of covariance. Correspondence analysis produced a qualitative view of categorical similarities and differences between systems thinking and personality traits. Systems thinking was then correlated with personality traits to identify correlation significance. Finally, analysis of covariance was employed to capture the relationship

between systems thinking and personality traits, while controlling for the expert-novice design experience. The covariate was freshmen, seniors and professionals.

Limitations of the Study

The first limitation of the study was in the systems coding. The researcher was the primary coder for the 61 design sessions, therefore researcher bias was inevitable. Two engineering education graduate students volunteered to be secondary coders for some sessions. The added coding allowed the researcher to compare his codes and receive external input from the graduate students. This helped reduce coding bias and coding fixation from the researcher. The second limitation was in the personality trait information obtained from the participants through the BFI personality survey. BFI is a form of self-evaluation and is prone to response bias (Mcdonald, 2008). Although an incentive was provided, participation in the survey was completely voluntary. Since the participants worked in teams of two, team personality data was only considered for analysis if *both* team members completed the survey. Eighteen out of 61 teams had complete survey results, which were used in the analysis of personality traits and systems thinking for research question 4. Engineers were anticipated to have about two dominant traits, as supported by the literature (Cárdenas Moren et al., 2019; Williams, 2009; Williamson, Lounsbury, & Han, 2013), therefore, absence of all possible combinations of personality traits was acceptable. The third limitation was in the assumption of participant ages. This information was not collected during data collection, therefore, the researcher assumed freshmen to be between 18-19 years old, seniors to be between 22-23 years old, and professionals with at least 10 years of work experience to be 45 years old. The ages were used to compare the BFI trait scores to a larger comparison sample

(Appendix C). Freshmen engineering students were compared to the minimum age available in the comparison sample, which was 21. This is covered in detail in Chapter III – Methodology. Due to limitations on BFI data, sample size, and assumptions on participant ages, research question 4 was framed as an exploratory research question.

Assumptions of the Study

Professional engineers who have worked in industry for more than 10 years or have 10,000 hours of experience were assumed to be experts because they have more design experience compared to engineering students; who were the novices with less design experience. This implied that if the two cohorts differed in systems thinking, then engineering design education can intervene to bridge the gap so that students design in a way that resemble experts.

Since engineering design aims to solve complex engineering problems, a systems approach to break the problems into smaller manageable problems (problem decomposition), and to synthesize smaller solutions into the bigger function or purpose (problem recomposition), is a natural behavior of design. In this view, systems thinking is assumed to be an inevitable event during engineering design.

Personality of an individual is assumed to be independent of the environment. This meant that designers designed in a way that reflected aspects of their personality. Furthermore, the two members of the team worked together to produce the final design solutions, therefore, the team is considered a unit and an average team personality score was computed for each team.

CHAPTER II

REVIEW OF LITERATURE

Overview and Selection Criteria

The body of literature on 'Systems Thinking' has increased over the past two decades as researchers show heightened interest in the topic. The literature review for this study was selective and focused on Systems Thinking of Experts and Novices. To establish a focal point for the study, systems thinking was narrowed to the context of engineering and engineering design. Therefore, the search for literature included filters like engineering, design, STEM, and engineering education. Sources of the literature included, however, not limited to, *Journal of Engineering Education, European Journal of Engineering Education, International Journal of Engineering Education, Design Studies, Institute of Electrical and Electronics Engineers (IEEE),* and *Research in Engineering Design*. Search engines and databases that were used for the literature review included Google Scholar, Wiley Online Library, Scopus, Science Direct, IEEE Xplore, EBSCOhost, and Academia.

Interrelated areas to systems thinking of experts and novices include problem decomposition and recomposition, problem space-solution space, team collaboration through member interactions, and personalities of systems thinkers. These interrelated areas served as key words and inclusion criteria in the literature search. It helped the researcher understand more about the topic being studied and provided a direction to identify the gaps in the literature. The literature review is organized into three sections. The first section reviewed the literature on the definitions of system and systems thinking

from various engineering disciplines and proposed working definitions for this study. The second section reviewed the current state of engineering design research and emphasized the importance of systems thinking in engineering design. Here, the interrelated areas are brought into perspective from the lens of systems thinking. The final section acknowledged the humanistic side of engineering design and reviewed literature in engineering education and systems engineering that related individual personalities to systems thinking.

System and Systems Thinking

Researchers define *system* differently based on their disciplinary backgrounds, their experiences, and the purpose of their study. To better understand a system in the context of engineering design, the researcher explored definitions of a system from various disciplines including systems architecture, systems engineering, control systems, design and management, and mechanical engineering design. Doing so had two benefits: 1) observe the patterns and similarities between the definitions; and 2) arrive at a consensus for what a system is in engineering design and propose a generic definition.

From the lens of systems architecture, Crawley et al. (2016) defined systems as: “a set of entities and their relationships, whose functionality is greater than the sum of the individual entities” (p. 9). This definition had two important parts: first, a system is made up of entities that interact or are interrelated, and second, when the entities interact, a function that is greater than the function of the individual entities emerged. Similarly, the International Council of Systems Engineering (INCOSE) (Higgins, 2004), defined a system as: “an integrated set of elements that accomplish a defined objective” (p. 10).

These elements include products (hardware, software, and firmware), processes, people, information, techniques, facilities, services, and other support elements. The scientific literature in control systems defined a system as an arrangement of physical components connected or related in such a manner as to form and/or act as an entire unit (DiStefano et al., 2012). From a design and management perspective, a system is a set of physical parts that are part of a bigger whole, e.g. the structural system of a building, or the traction control system of an automobile (Chan, 2015). In fracture mechanics, when designing a system, one should realize that the interaction of material properties, such as the fracture toughness, the design stress, and crack size, control the conditions for fracture in a component (Hertzberg, Vinci, & Hertzberg, 2013). Here, fracture toughness, stress, and crack size are the elements that work together to produce the function - fracture, although undesired in some cases, it is inevitable in engineering material design.

Despite slight variations in their definitions of a system, they overlap in the sense that a system is a collection and cooperation of smaller elements that work together to produce some desired function or outcome. Smaller elements refer to solution elements such as subsystems, parts, and components as defined by INCOSE (Higgins, 2004). Based on the definitions above, a system can loosely be defined as *the interaction of solution elements to achieve some higher order function* and is the working definition of a system for this study.

Systems thinking takes on a cognitive stance at how to solve a complex system (Behl & Ferreira, 2014; Chan, 2015; Crawley et al., 2016; Rouse, 2003; Ryen, 2008). It is considered a cognitive activity because it involves various modes of reasoning such as critical reasoning - evaluating the validity of claims, analytical reasoning - analysis from

a set of laws or principles, and creative thinking – thinking outside of the box (Crawley et al., 2016). Furthermore, it is also the mental capacity and ability of designers and engineers to treat problems as complex, and to see the system as a whole, rather than in part (Behl & Ferreira, 2014). Seeing the system as a whole is synonymous with what other authors referred to as ‘a big picture view’ of the complex system (Chan, 2015) and ‘holistic view’ of the system (Godfrey et al., 2014; Robinson-Bryant, 2018).

Systems thinking as a holistic view help designers and engineers focus on the relationships of the entities and the emergence of the desirable functions or outputs of these relationships (Crawley et al., 2016). Similarly, Chan (2015) argues that embracing a big picture view enabled system thinking, which allowed one to comprehend the coherence and synergy of the system to produce the desired function. A big picture view is embedded in one of the systems engineering principles - to start with your eye on the finish line (Ryen, 2008); where the function or desirable outputs of the system (the finish line) should be the primary focus because it dictates the successfulness of that system. However, this does not imply a linear view of the subsystems and solution elements that synthesize to the functions of the system. Instead, systems thinking is iterative and seeks to understand interconnections (of solution elements) through a closed-loop circular view (Frank, 2006). Simply put, there are multiple ways to obtain the functions or desirable outputs, but it is up to the designers and engineers to reason, view, and understand the complex system through a systems thinking approach (Crawley et al., 2016; Frank, 2006).

Good problem-solvers and designers should be associated with maintaining sight of the big picture by including systems thinking in engineering design (Dym et al., 2006).

Systems thinking has practical implications because it is viewed as a *skill* to understand, manage, and solve real-world engineering problems (Frank, Sadeh, & Ashkenasi, 2011; Robinson-Bryant, 2018; Simpson & Martins, 2011). According to the authors, real-world engineering design problems are practical, complex, ill-structured, and multidisciplinary. Therefore, systems thinking is a way to manage and solve complex engineering design problems. In both views, systems thinking as a skill or systems thinking as a cognitive activity, the idea of embracing a big picture or a holistic view is evident.

Systems thinking as a big picture or holistic view converge to what Rouse (2003) called a ‘Hierarchical Mappings’ view of complex systems in engineering design. In this view, the approach to solving the complex system is problem decomposition and the focus is on engineering solutions - the big picture. Problem decomposition is the process of dividing and conquering the interacting elements in the system hierarchy into smaller manageable sub-problems. The interacting elements, referred to as *solution elements* in the definition of a system, eventually compose or synthesize to form the system behavior, system function, or system output. In summary, systems thinking is *a hierarchical view of a complex system that can be decomposed into subsystems and smaller components*. This is the working definition of systems thinking for this study.

The result of applying systems thinking is good decision making (Chang & Chuang, 2018; Dawidowicz, 2011) and increased project success (Bar-yam, 2003; Davidz, 2006; Frank et al., 2011; Ribrant & Bertling, 2007; Slegers et al., 2012). Frank, Sadeh, & Ashkenasi (2011) conducted a study where they recruited 114 senior systems engineers to participate in a self-reported questionnaire. The questionnaire measured capacity for engineering systems thinking, project success, and project type. A significant

correlation was found between the capacity for engineering systems thinking and project success. They concluded that engineers who have the capacity for systems thinking are most needed in new generation and innovative projects. Project success was based on measures of efficiency, customer, team, business, future, and public relations. Their conclusion reinforced the claim made by other authors that systems thinking is an important skill for project success (Bar-yam, 2003; Davidz, 2006; Ribrant & Bertling, 2007; Slegers et al., 2012). However, their findings suggest little evidence as to where and how this skill, ability, or capacity to systems think came about. In response, some authors embrace a dual view and suggest that while company culture is responsible for it, engineering education is the key to unlock systems thinking (Chang & Chuang, 2018; Robinson-Bryant, 2018; Simpson & Martins, 2011; Wasson, 2012).

Systems Thinking and Engineering Education

Systems thinking can be viewed as a cognitive ability (Behl & Ferreira, 2014; Chan, 2015; Crawley et al., 2016; Rouse, 2003; Ryen, 2008), as well as a practical skill (Frank, Sadeh, & Ashkenasi, 2011; Robinson-Bryant, 2018; Simpson & Martins, 2011). The importance of systems thinking is identified as a missing competency in engineering graduates (Robinson-Bryant, 2018; Simpson & Martins, 2011; Wasson, 2012) and researchers, engineers, and government agencies look to engineering education as a solution to fill this void. For example, ABET (2018), an accreditation board for engineering and technology for post-secondary education, stated that students should have “an ability to identify, formulate, and solve *complex engineering problems* by applying principles of engineering, science, and mathematics” (p. 5). Some universities

tackled this endeavor from a system engineering perspective, but they encountered many challenges.

Some universities have established their own systems engineering programs (Ng, 2003), however, they find it challenging to integrate systems thinking into their engineering curriculum given their already overwhelming amount of important materials to cover (Simpson & Martins, 2011). Furthermore, engineering design education finds it difficult for students to learn design thinking, and even harder to teach (Dym et al., 2006). Despite evidence in support of project-based learning as a successful design pedagogy to improve student learning, resource allocation (e.g. faculties and facilities) towards design pedagogy remain low on priority (Dym et al., 2006). On the other hand, existing design pedagogies face criticism. Critics argue that systems thinking and systems design require an engineering education that achieves competence rather than specialization in subject knowledge (Godfrey et al., 2014). This requires an ability to learn and progress through an open-ended, formative, and dynamic learning process rather than the traditional 'rote' application of pre-defined knowledge (Godfrey et al., 2014). Additionally, Robinson-Bryant (2018) and Wasson (2012) assert that traditional engineering programs lack formal engineering education to help students understand the holistic implications of ill-structured problems, which students are likely to encounter after graduation. In fact, engineers spend 70-80% of their careers solving complex systems engineering problems, but they lack the competencies required for the job (Wasson, 2012).

Industry also play a role in shaping engineering education. As systems become more complex, companies like Microsoft and Boeing (Crawley et al., 2016), are faced

with challenges to develop systems thinking capability of their workforce (Heidi & Martin, 2011). Additionally, companies recruit engineers with systems thinking capabilities such as systems engineers (Gonçalves & Britz, 2009). The assumption here is that systems engineers are unique and possess systems thinking skills (Frank, 2000). The lack of systems thinking capability of the workforce is aggravated as senior practitioners are approaching retirement, creating a need for rapid development of systems engineering expertise to replace the senior systems engineers (Armstrong & Wade, 2015). Consequently, this need is relayed to engineering education.

An influx in demand for systems thinking in engineering education is inevitable. For example, Simpson and Martins (2011) saw that design of complex engineered systems have evolved remarkably over the past two decades. In their efforts to overcome the challenges that they were facing, they gathered 48 people from industry, academia, and government agencies to a workshop. The workshop concluded with five recommendations, among which one of them was to better educate students to think in a systems perspective. They urge faculty to be creative in assignments and textbooks to help foster students to think in a system view that synthesizes the details towards the big picture (or 'outputs' in their words) instead of analyzing the details. Other authors were not as specific as Simpson and Martins (2011), and briefly conclude with building an allegiance with engineering education for this endeavor (Chang & Chuang, 2018; Robinson-Bryant, 2018; Wasson, 2012).

Despite challenges to incorporate systems thinking in engineering education, research and implementation of systems thinking is an on-going effort. Robinson-Bryant (2018) implemented a systems thinking skills intervention to 3rd and 4th year engineering

students who were enrolled in an online project management course. The intervention purports to foster 'deep, connected, and coherent' learning to systems thinking skills. The implementation is currently a work in progress. Research has shown that there have been some successful cases to incorporate elements of systems thinking into engineering curriculum. A pilot study of 68 engineering students showed an increase in systems thinking after completing an assignment that required the development of a systems architecture (Godfrey et al., 2014). Systems thinking was measured in terms of learning power, which consisted of dimensions such as creativity and learning relationships. Furthermore, Hayden et al. (2011) were successful at integrating systems thinking into their civil and environment engineering program at the first-year introductory level and senior year design courses. As a result, they found that students were able to transfer their skills from earlier education to senior design projects.

These successes came with challenges as well as opportunities to improve engineering education (Camelia, Ferris, & Behrend, 2020; Camelia, Ferris, & Member, 2017; Hayden et al., 2011). One opportunity is to better understand expert knowledge of systems thinking and comparing with novices to identify the gaps that exist between experts and novices (Dixon & Johnson, 2011; Haupt, 2015; Lammi & Thornton, 2013; Song, 2014). However, expert time is a challenge for researchers to obtain and recruit, as a result, few studies in engineering education have expert data on systems thinking. In most of the literature reviewed, experts were professional engineers that acquired at least 10 years of work experience and novices referred to students enrolled in an undergraduate engineering program. The assumption is that experts are more

knowledgeable and more experienced, therefore, novices should seek to think and problem-solve like experts.

Expert vs Novice

From as early as the 1980s, researchers acknowledged that the transition from novice to expert is continuous, and that intermediate stages of expertise exist between novices on the one end to experts on the other end (Dreyfus & Dreyfus, 1986; Hoffman, 1998). In other words, a hierarchy exists between experts and novices. Different terms have been used to describe the intermediate stages, for example Dreyfus & Dreyfus (1986) described the hierarchy in 5 stages: novice, advanced beginner, competence, proficiency, and expertise. Additionally, cognitive psychology assert that there are stages before and after novices and experts, the stages are: naivette, novice, initiate, apprentice, journeyman, expert, and master (Hoffman, 1998). 'Naivette' is one who is totally ignorant of the domain, whereas 'master' is an elite group of experts who set the regulations, standards, and ideals. Despite the differences in labeling the various milestones, the progression from one stage to the next from novice to expert is apparent.

In the engineering education literature, the intermediate stages between novices and experts have rarely been identified. Researchers have labeled participants as 'novices' to group engineering students and 'experts' to group professional engineers with at least 10 years of professional practice (Atman et al., 2007; Becker et al., 2019; Dixon & Johnson, 2011; Haupt, 2015; Ho, 2001; Song, 2014). Some studies distinguished their participants into three groups, freshmen students, senior students, and expert engineers, where the seniors are viewed as the intermediate cohort between the

novice freshmen and expert engineers (Atman et al., 2007; Becker et al., 2019; Song, 2014). Their studies measured design processes (Atman et al., 2007), design cognition in terms of function-behavior-structure (Becker et al., 2019; Song, 2014) and problem decomposition (Ho, 2001; Song, 2014) for complex design problems. However, little reference was made to systems thinking, although some of their findings, such as problem scoping and problem decomposition are relevant in the systems thinking literature.

Problem Decomposition/Recomposition

A term commonly used in design to describe the processes of systems thinking is problem decomposition. According to INCOSE (Higgins, 2004), decomposition is a top-down approach to solve complex systems by decomposing a high level system or problem into solution elements. Figure 1 shows an example of hierarchies within a system that was used in the INCOSE systems engineering handbook. Using Figure 1, and the added annotations, problem decomposition is a top-down process of decomposing a system into solution elements. Solution elements consist of elements, subsystems, assemblies, components, and parts. During design, it is common to begin solving problems with a systems decomposition approach by focusing on the big picture and then venturing into details (Gralla, Herrmann, & Morency, 2017). On the other hand, problem recomposition is the reverse of problem decomposition, it is a bottom-up approach. Problem recomposition synthesizes solution elements at the lower levels of the system hierarchy (e.g. parts, components, and assemblies in Figure 1) to higher levels of the system hierarchy (e.g. subsystems and elements in Figure 1). Problem decomposition and recomposition are complementary because they both describe the same solution elements,

but differ in whether it is a top-down process (decomposition) or bottom-up process (recomposition). In engineering design studies, both measures are used to understand how designers think and problem solve during the iterative design process (Song, 2014).

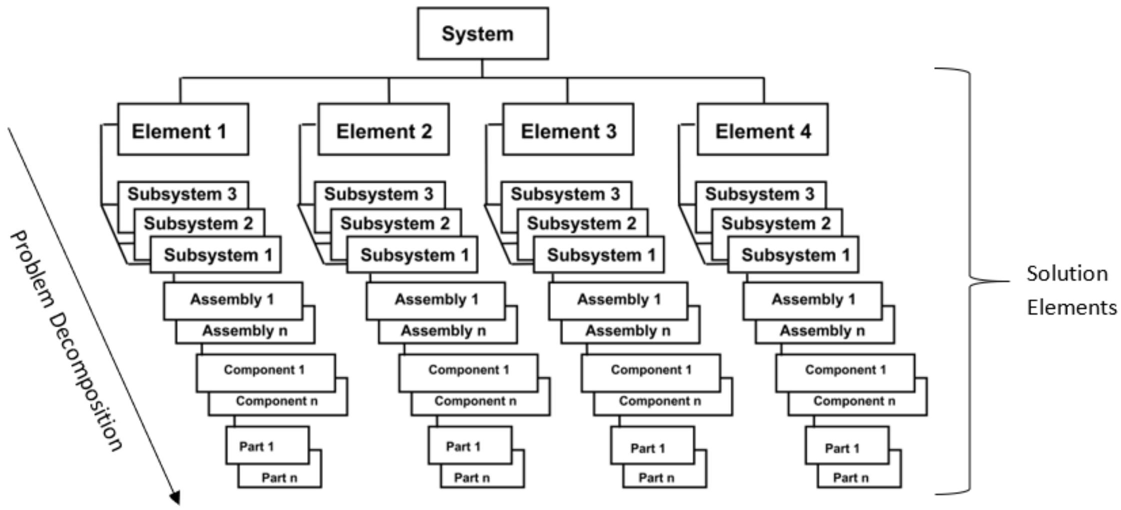


Figure 1. INCOSE – System Hierarchy (Higgins, 2004)

Decomposition is a problem-solving strategy – it decomposes a complex problem into smaller and manageable solution elements within the system hierarchy (Higgins, 2004). These solution elements are usually well-known or well-designed structures or solutions that already exist (Rouse, 2003). Consequently, many decomposition strategies exist. The existence of many decomposition strategies makes it challenging for researchers to compare studies, in particular, expert-novice studies, because such studies inform engineering education in areas of design cognition (Becker et al., 2019; Dixon & Johnson, 2011; Lammi & Thornton, 2013) and problem decomposition (Ho, 2001; Song, 2014).

Several studies have shown that problem decomposition is a universal language among expert engineers (Gralla et al., 2017; Tobias, Herrmann, & Gralla, 2015). A study

of small teams of facility designers found that most teams start at a problem decomposition level, but lack consistency among the teams, and are unable to identify the best ways to decompose the problem into solution elements (Gralla et al., 2017). Similarly, Tobias, Herrmann, and Gralla, (2015) challenged teams of professional engineers to redesign a manufacturing facility and found that professional engineers preferred implicit decomposition over explicit decomposition. Implicit decomposition occurs where structures (or solution elements) of the problem are created throughout the design process rather than being defined in the beginning, which is explicit decomposition (Ho, 2001). In cases where explicit decompositions were utilized, it was found that some teams were 'incomplete' in their decomposition process because they implemented decompositions that was not discussed among the team members (Tobias et al., 2015).

In problem decomposition of experts and novices, it was found that focus on design functions, outputs, and goals tends to be a behavior of experts in solving design problems. Experts adopted a top-down or problem decomposition approach to problem-solving, and novices preferred the reverse, which is a bottom-up or problem recomposition approach (Atman et al., 2007; Dixon, 2011; Ho, 2001; Song, 2014). A dominant characteristic that distinguishes systems thinking among expert engineers is their ability to "think broadly" (Davidz, 2006). Experts are capable of this because of their breadth of knowledge and understanding of multiple aspects and levels of the problem (Armstrong & Wade, 2015). In engineering design, experts demonstrate this by primarily using problem decomposition strategies to solve the broad, complex, and ill-structured problems (Ho, 2001). Problems that are higher up in the systems hierarchy are

identified and decomposed into solution elements. On the contrary, novice designers, such as engineering students, primarily use a bottom-up or problem recomposition approach. Additionally, a pilot study found that both novices and experts performed problem decomposition and recomposition, however, both strategies were found to be significantly less for engineering students compared to that of experts (Song, 2014). The findings shed light on another noticeable difference between expert and novice design behavior – problem focus and solution focus.

Problem-Solution Focus

During design, the designer either tries to understand the problem - problem space or find solutions to the problem - solution space (Jiang et al., 2014). Studies found that experts and novices differed in allocating time in the problem space and solution space. Experts tend to spend more cognitive effort on problem scoping and information gathering compared to that of students (Atman et al., 2007; Becker et al., 2019). Through verbal protocol analysis, Atman et al. (2007) measured the time spent in problem scoping for experts engineers and engineers students when designing a playground. They found that experts spent almost twice as much time in the problem scoping activities such as problem definition and information gathering compared to that of students. The result illustrates that experts spent a significant amount of effort to formulate the nature of the problem.

This conclusion was echoed in a recent study that used the Function-Behavior-Structure (FBS) Ontology to measure differences in design cognition between experts and novices when designing a window opening device (Becker et al., 2019). Through

verbal protocol analysis and FBS problem-solution space analysis (Jiang et al., 2014), the authors found that experts spent more cognitive effort in the problem-space compared to that of novices. Moreover, the results of their temporal analysis on problem-solution focus showed that experts were consistently higher in problem-focus throughout the one-hour design session compared to novices.

In contrast, an exploratory study between an expert and a novice showed that the novice spent more time in the problem space than the expert (Dixon, 2011). Both participants were asked to design a mechanical release device while thinking aloud for one hour. From verbal protocol analysis, the author found that the novice used a problem-driven strategy because he mainly depended on the information provided by the problem statement. On the other hand, the expert used a solution-driven approach and spent most of his time generating solutions. The results here were based on the responses of two participants, one expert and one novice. Whether the results here would be replicated by other participants remain in question.

Mixed results have been found for problem-solution focus of experts and novices in engineering design. Some studies found that experts focus on the problem space more than novices (Atman et al., 2007; Becker et al., 2019), while other studies contradict this claim (Dixon, 2011). More studies on problem-solution focus of experts and novices are required to adequately understand this design behavior. Problem-solution focus of experts and novices in systems thinking remain unexplored. However, this alone is insufficient to understand expert design in practice. When design problems get overly complex, experts look beyond their individual understanding of the problem and solutions. They rely on

teams of diverse expertise to expand their domain knowledge and ideas. This is discussed in the next section.

Team Interactions in Engineering Design

Teams are considered to be a necessary feature of engineering, especially when solving dynamic and complex problems (Gyory, Cagan, & Kotovsky, 2019; Hsu, 2017; Lerdahl, 2001; Oladirana, Uziaka, Eisenbergb, & Schefferc, 2011). In practice, engineering design teams are encouraged to develop and construct design solutions through collaboration of individual expert knowledge and experience (Flanagan, Eckert, & Clarkson, 2007), creativity (Lerdahl, 2001), and work values (Hsu, 2017). Engineering education incorporated teamwork into the classroom by forming design teams in senior capstone classes, which have shown to have positive learning opportunities for students (Howe & College, 2010). In the formation of design teams, studies stressed the importance of multidisciplinary teams (Hotaling, Burks Fasse, & Bost F., 2012), gender-diverse teams (J. Gero & Milovanovic, 2019), and personality-diverse teams (Shen, Prior, White, & Karamanoglu, 2013; C. A. Toh & Miller, 2016; Trenshaw & Vogel, 2014; Varvel, Adams, Pridie, & Ruiz Ulloa, 2004). However, few studies have been done in engineering education to compare expert teams and novice teams while designing.

In the literature review, numerous expert-novice design studies have been done, however, only a few studies incorporated teams in their experimental design. A majority of the studies had the participants work as individuals to solve a design problem. Among the studies that involved expert design teams in engineering design, differences were found in problem decomposition (Song, 2014), problem-solution focus (Becker et al.,

2019), problem representation (Popovic & Kraal, 2010), and theme extraction; where themes referred to social awareness such as hygiene, ease of use, and sustainability (Dorst & Hansen, 2011). Although differences were found between expert and novice design teams, the interactions of expert and novice design teams was not addressed. Moreover, evidence in a recent study illustrate that design team interactions is an area that deserves more attention from engineering education researchers.

A model was developed by Gero & Milovanovic (2019) using situated Function-Behavior-Structure to capture designer interactions for co-design activity. Co-design was defined to be a process of a team member enacting upon another team member's idea. Using the model, they investigated the effect of gender diversity in design team interactions. Team interactions were measured by turn-taking between two members of the team during the design session. Teams with all males were compared to teams with one male and one female. In their analysis of 28 design teams, they found that teams with males and females had significantly more co-design activities than teams with both males (Milovanovic & Gero, 2019). This study measured the effect of gender diversity on co-design activity and the methodology developed in the study could be extended to explore the co-design activity of expert and novice design teams.

On the contrary, some argue that collaborative teams in practice may not be optimal in every circumstance, and that proper process management is required for teams to be effective (Gyory et al., 2019). Additionally, teams are composed of complex individuals and performance of the team depends on the organization and synergy of individual members of the team (Sanchez-Segura, Hadzikadic, Dugarte-Peña, & Medina-Dominguez, 2018). In fact, individual personalities affect the performance and

effectiveness of design teams (DuPont & Hoyle, 2015; O'Neill & Allen, 2011; Shen et al., 2013; C. Toh, Miller, & Kremer, 2013; Trenshaw & Vogel, 2014; Varvel et al., 2004). This invites the discussion of individual personalities in the design of complex engineering problems. As alluded earlier in the literature, systems thinking is coupled with the design of complex engineering problems. Therefore, one would suspect that a relationship exists between individual personalities and systems thinking, and the literature review shows evidence of this relationship.

Systems Thinking and Individual Personality

Research shows that in addition to work experience and education, successful systems engineers and systems thinkers possess personalities and individual characteristics that enable them to perform systems thinking (Armstrong & Wade, 2015; Behl & Ferreira, 2014; Davidz, 2006; Frank, 2000, 2006; Heidi & Martin, 2011). According to Davidz (2006) and Frank (2006), systems thinking; the knowledge, abilities, and competencies, is a mixture of "innate" and acquired experience. "Innate" referred to individual characteristics and personalities that are independent of acquired experiences or education. An analysis on systems thinking key factors indicated that individual elements such as big picture minded, good communication skills, self-confident, and good listening skills are key to systems thinking (Behl & Ferreira, 2014). Results of interviews conducted by Armstrong & Wade (2015) with systems engineers indicated that systems thinking expertise are found in individuals that develop, among others, a breadth of knowledge and indulge in unstructured and self-directed learning. Additionally, the ability to work in teams, having good human relations, and a mindset

for lifelong learning, are also personality characteristics that enabled systems thinking (Frank, 2000).

Industry has acknowledged the relationship between personality characteristics and systems thinking. As a result, they are selective in their screening process for systems engineers so that the development of systems thinking capabilities in their workforce is accelerated (Davidz, 2006; Gonçalves & Britz, 2009). Systems engineering candidates should possess certain desirable personality characteristics and cognitive abilities to have sufficient ‘potential’ to become a competent system engineer (Gonçalves & Britz, 2009). The authors grouped the characteristics into intra- and inter-personal characteristics. Intra-personal characteristics referred to attributes relating to self - such as intellectual curiosity, creativity, big picture thinking, and systems thinking. Inter-personal characteristics referred attributes relating to others - such as leadership skills, extroversion, and persuasiveness.

Davidz (2006) realized that the personalities of the engineers are inadequately studied and proposed that such information would draw insight to what makes systems engineers successful. A majority of the studies used formal and informal interviews to solicit enablers, key factors, and elements to systems thinking of professional engineers from various engineering disciplines (Armstrong & Wade, 2015; Behl & Ferreira, 2014; Davidz, 2006; Frank, 2000, 2006; Heidi & Martin, 2011). In these studies, participant responses were drawn from their personal experiences and gave descriptions of the characteristics, attitudes, skills, and knowledge that successful systems engineer ought to have. The literature suggests some evidence of a relationship between individual personalities and systems thinking, however, it lacks a consistent way to measure the

personalities of engineers and relating it to systems thinking. To better understand systems thinking as an innate ability (Davidz, 2006; Frank, 2006), more studies are needed to examine the personalities of engineers.

Studies have shown that engineers have personalities that differ to those of the general population. In fact, they exhibit strong preferences for some types of behaviors. Engineers are mostly introverts and prefer judgement over perception (Knauerhase & Hahn, 2008). They have strong identification with authority and are tough-minded (Williams, 2009). On the Big Five personality tests, they score high on emotional stability and conscientiousness but lower in agreeableness (Van Der Molen, Schmidt, & Kruisman, 2007). Furthermore, studies have shown that engineers and engineering students have about two dominant personality traits that stand out from the other traits, namely high conscientiousness and emotionally stable (Cárdenas Moren et al., 2019; Williams, 2009; Williamson et al., 2013).

Summary

This chapter adopted a working definition of systems thinking as a hierarchical view of a complex system that can be decomposed into subsystems and smaller components. Systems thinking is an important cognitive ability, skill, and competency that is lacking in the engineering workforce and engineering graduates. However, researchers believe that systems thinking can be developed through work experience of engineers and engineering education of students. Expert systems thinkers that have many years of experience set the benchmark for novice engineering students that lack systems thinking experience. From engineering design studies, differences in expert-novice

problem decomposition strategies, problem-solution focus, and the ability to work in teams, hold evidence for different expert-novice systems thinking. However, expert-novice systems thinking in the designing of complex engineering systems is understudied in engineering education. Therefore, more studies are needed to better understand the systems thinking process of experts and novices in order to inform future engineering education. Additionally, personalities and characteristics such as being creative, open-minded, big-picture minded, and good soft skills, were believed to benefit systems thinking. However, the relationship between systems thinking and individual personalities is unclear as the studies conclude that individual personalities is just one of many factors that contribute to systems thinking. Given the unclarity in this relationship, and a narrow pool of the personalities of engineers, the relationship warrants further investigation.

CHAPTER III

METHODOLOGY

The knowledge, abilities, and competencies of systems thinking is a mixture of acquired experience and individual personalities (Davidz, 2006; Frank, 2006). Acquired engineering experience is achievable over time with exposure to systems architecture, systems processes, systems culture of the organization, and regular engineering work (Wasson, 2012). One of the underlying assumptions of this research is that professional engineers, who have worked in industry for more than 10 years, have more design experience than engineering students, and overtime, systems engineering is improved. On the contrary, individual personality traits are stable over time (Soldz & Vaillant, 1999), and as illustrated in the literature review, it is considered to be an important factor for successful systems engineering (Armstrong & Wade, 2015; Behl & Ferreira, 2014; Davidz, 2006; Frank, 2000, 2006; Frank et al., 2011; Heidi & Martin, 2011).

The methodology section is organized into two parts. Since differences were found in systems thinking between engineering experts and novices while solving design problems (Ho, 2001; Song, 2014), the first part focused on systems thinking of professional engineers and engineering students. Consistent with Ho (2001) and Song's (2012) study, professional engineers are referred to as 'experts' and engineering students are referred to as 'novices' – both are used interchangeably throughout the document. This embedded an assumption that professional engineers are experts because they have more design experience compared to engineering students. The second part is framed as a pilot study that explored relationships between systems thinking and personality traits.

Using tools developed from Function-Behavior-Structure (FBS) (J. S. Gero, 1990) and existing FBS coded data, systems level codes were generated through a systems hierarchy coding scheme similar to that of Gero & Mc Neill (1998), Ho (2001), and Song (2014). These system level codes formed the database for statistical analysis. Measurements and analyses of systems thinking of experts and novices were guided by the following research questions and hypotheses:

Research Questions 1 – 3:

1. What are the differences in systems thinking between professional engineers and engineering students when solving engineering design problems?

   H1: Professional engineers will use problem decomposition and recomposition more than engineering students.

2. What are the differences in systems cognitive effort between professional engineers and engineering students related to FBS problem space and solution space?

   H2: Professional engineers will have more systems level 1 in the "FBS Issues" problem space than engineering students.

   H3: Professional engineers will have more problem decomposition in the "FBS Processes" problem space than engineering students.

3. How do team member interactions affect problem decomposition and recomposition?

H4: Professional engineers will use problem decomposition more as team interactions increase compared to engineering students.

The second part of the study involved the collection of the Big Five personality information from the participants (see Data Collection section for details). With the systems level codes generated, and the Big Five personality information collected, relationships between personality traits and systems thinking were investigated and guided by the following research question:

Research Question 4:

4. What is the relationship between the Big Five personality traits and systems thinking in engineering design?

Research questions 1 - 3 are quantitative and involved hypothesis testing. Both research questions and hypotheses are included because the hypotheses purport to go beyond and build on the research questions. Since they investigated the differences between two variables, systems thinking and expert-novice, it required a quantitative approach (Johnson & Christensen, 2017). Despite a quantitative analysis, the original data that was obtained from protocol study is qualitative. The FBS coding scheme was used to quantify the qualitative data in a uniform way (J. S. Gero & Kannengiesser, 2007). The FBS coded sessions underwent systems hierarchy coding, which formed the database for analysis. FBS Ontology is discussed next.

Function-Behavior-Structure (FBS) Ontology

FBS is an instrument used to measure design. Just like how a thermometer measures temperature and a watch measures time, FBS measures design. The FBS design ontology describes all designed issues, or artefacts, irrespective of the specific discipline (J. S. Gero & Kannengiesser, 2007). It is a uniform way to characterize and measure designing in three fundamental constructs – Function, Behavior, and Structure. The goal of designing is to transform a set of functions, driven by client requirements (R) into a set of descriptions (D). Function (F) is the intended teleology or “what the artefact is for”. Behavior is “what the artefact does” and provides measurable criteria for comparison. Designers decide which behaviors are significant and needed to assess the designs they produce. Therefore, there are two types of behaviors; it can either be expected behavior (Be), which is the measurable outcome set by expectations, or derived behavior from the structure (Bs), which is what the artefact actually does. The Structure (S) is the physical components and their relationships or “what the object consists of”. The six codes, F, Be, Bs, S, R, and D, are referred to as “FBS Issues” and provide the basis for coding design protocols. See example of FBS Issues in Figure 2 and a summary of definitions in Table 1.

Figure 2. Example of FBS Using a Phone

Table 1

FBS Issues Definition and Examples (using Figure 2)

FBS Issue	Code	Definition	Example
Function	F	The intended teleology or purpose	• Ease of navigation • Ease of carrying phone in pocket
Expected Behavior	Be	A measurable outcome set by expectations	• One degree of freedom to go to home menu • Reduced volume of the phone case
Behavior from Structure	Bs	Behavior of the structure i.e. what the structure does	• Phone *rings* • Phone *vibrates*
Structure	S	The physical components and their relationships	• Phone • Home Button • Length, width, thickness
Requirements	R	Client requirements	• Comply with ADA and safety standards
Documentation	D	Descriptions or documentation	• Designer takes note or document his/her work

FBS Issues further extend to FBS transformations (J. S. Gero & Kannengiesser, 2014), or what the authors called “FBS Processes” during design. This occurs when designers move from one FBS Issue to the next. For example, a basic transformation from function to expected behavior (F > Be) translates a set of desired goals into measurable behavior or outcomes. In other words, FBS process is a way to capture the relationship between the function (F) and expected behavior (Be). Relationships or “transformations” between other FBS issue also exist. This is shown in Figure 3, FBS Framework (Gero, 1990; J. S. Gero & Kannengiesser, 2014), and summarized with their definitions in Table 2.

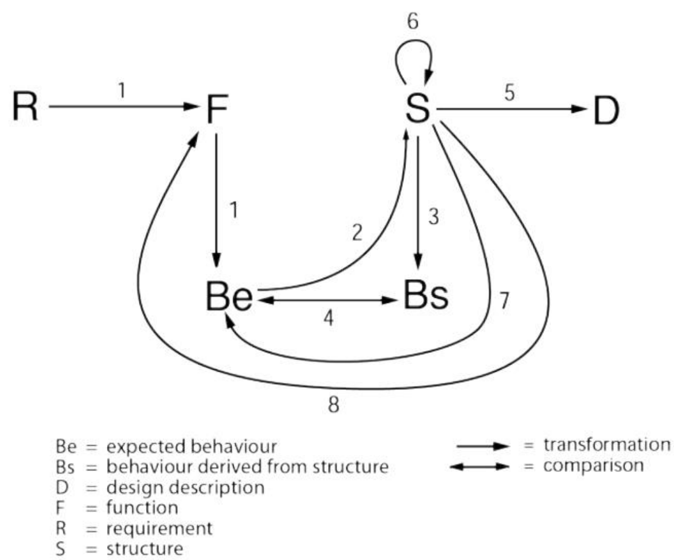


Figure 3. FBS Framework

Table 2

FBS Transformations

Label	Process	Terminology	Definition
(1) (1)	R → F F → Be	Formulation	Interpretation of external requirements set by the client and the generation of additional implicit requirements or expectations
(2)	Be → S	Synthesis	Expected behavior is used in selection and combination of structure to determine specific object design variables, search methods, and final results
(3)	S → Bs	Analysis	Interprets the structure of the process and determines what actual performance or behavior of the structures are
(4)	Be ↔ Bs	Evaluation	Compares actual performance against expected performance
(5)	S → D	Documentation	Externalize representations of the final design for purpose of communication
(6)	S → S	Reformulation 1	Reformulates structure – usually done when performance is unsatisfactory
(7)	S → Be	Reformulation 2	Reformulates behavior – usually driven by unsatisfactory project constraints
(8)	S → F	Reformulation 3	Reformulates function – usually driven by unsatisfactory requirements

FBS and Systems Thinking

Chan (2015) asserts that Function-Behavior and part-whole structure rank among the top foundational concepts of systems thinking. Part-whole structure means that parts

of a system can be decomposed into sub-systems and recomposed in a bottom-up fashion until the top-level system is reached. Function and behavior acknowledge that engineered systems are designed for a purpose. Structures with their functions are put together to produce some change. The change that result from this is the behavior observed in the system. In this view, systems are treated as a hierarchy because the parts of the system are arranged in a hierarchical manner. Similarly, International Council of Systems Engineering (INCOSE) (Higgins, 2004) adopted a systems hierarchical approach in defining their system, where a complex system is decomposed into elements, subsystems, which are further decomposed into components and parts (see Figure 1). An element is a major product, service, or facility of the system. A subsystem is an integrated set of assemblies, components and parts. According to INCOSE, the levels within the system hierarchies may vary depending on the complexity of the system; simple systems may have fewer levels than complex systems (Higgins, 2004).

In view of systems as hierarchies, the tools developed to measure systems thinking in engineering design should take into account the various hierarchies that exist within a system. Gero & Mc Neill (1998) developed a way to analyze design problems into various levels of abstraction in the problem domain. The designer's attention shifts from a high-level view of the problem to a low-level view of the problem. High-level view occurred when the designer considers the problem at the functional or systems level with a wholistic view. Low-level view occurred when the designer considers the problem at the details level. The authors defined the various levels by assigning a number to a level of the problem. This is summarized in Figure 4, where level 0 is the systems level (high-level view), level 1 is the interactions, level 2 is the sub-systems, and level 3 is the

details (low-level view). This method was used in Ho (2001) and Song (2014) who conducted similar protocol studies in engineering design, where they compared expert and novice designers' approach to solving engineering design problems. The authors concluded that experts focused more at the high-level functions and goals of the problem compared to novices.

Level of Abstraction

0	- *System*	The designer is considering the system as a whole.
1	- *Interactions*	The designer is considering the interactions between the sub-systems.
2	- *Sub-systems*	The designer is considering details of the sub-systems.
3	- *Details*	The designer is considering the detailed workings of a sub-system.
R	- *Requirements*	The designer is modifying or reconsidering aspects of the initial requirements.

Figure 4. Systems Levels in the Problem Domain (Gero & Mc Neill, 1998)

This study condensed the four levels of abstraction (0, 1, 2, 3 in Figure 4) to three new levels: 1, 2 and 3. Specifically, Level 0 became level 1, Level 1 and 2 was merged to level 2, and level 3 remained as level 3. The four levels were condensed to better distinguish the system hierarchy at the system level - the top level, subsystem level – the middle level, and details level – the bottom level. Level 0 and level 1 (in Figure 4) was merged to a single level - level 2, because subsystems and interactions between subsystems occur at the same level of the hierarchy, which is the subsystems level. The three new levels are referred to as system levels for the rest of the document. Requirements (R) was contextual and could either be system level 1, 2, 3 or O, where O described utterances that did not incorporate the design problem at any system level. An example would be Documentation (D) from FBS Issues. D occurred when designers took notes on paper or wrote on the whiteboard. It served as external memory and did not contribute anything new to their design nor describe the problem at any system level.

Therefore, “O” was a code assigned to D as well as other utterances that did not pertain to any systems level. Coding using the system levels 1, 2, 3 and O are discussed next.

Systems Hierarchy Coding

System levels 1, 2, 3 and O guided the systems hierarchy coding for this research and are summarized in Table 3. Description of the code are provided, however, the actual coding required coders to use Table 3 within context as exemplified by Figure 5. Example A of Figure 5 was a dialogue between two senior engineering students, at approximately16 minutes into the design session, where they discussed the possibility of using a lever-type system to help open the “sticky” window. The explanations (column F) or reasons for the systems level codes (column E) are more straightforward and therefore easy to interpret. However, this was not always the case for other design teams such as Example B, which was a dialogue between two freshmen engineering students where they evaluated their clamp system and discussed user interactions. Some utterances resulted in coder disagreements, for example row 4 of Example B.

Table 3

System Levels

Level	Systems Hierarchy	Description
1	System	The designer is considering the system as a whole. This is the top-level view as the designer is obtaining a holistic or big-picture view of the problem
2	Subsystems and their interactions	The designer is considering the subsystems and their interactions. This is the middle-level view as the designer is breaking the complex system into smaller and manageable subsystems
3	Details	The designer is considering the details of the subsystems. This is the low-level view as the designer is working out details of the subsystems such as size, dimensions, mathematic analysis, etc.
O	N/A	The designer is not considering the problem at levels 1, 2 or 3

In example B, it was clear from row 2 and 3 that their system was a clamp and both coders (coder 1 and coder 2) agreed on system level 1 (column E). However, there was a disagreement in row 4 where coder 1 (column F) thought the idea of being “strong enough to hold” should be at system level 2, whereas coder 2 (column G) thought it should be at system level 1. The coders came to an agreement that it should be at system level 1 because an evaluation about the system - the clamp, is at the systems level or level

1. Rows 5-7 was coded as systems level 2 because they described the subsystems – the window and the user, and the user interactions to get the window closed.

Example A. Senior Students

	A	B	C	D	E	F
1	Time	Person		FBS Code	Systems Level	Explanation
2		A	Is there like a lever system that we could put in there that could be easy?	S	1	lever is the system that they are discussing
3		B	Umm...you could do like a jack type of system.	S	1	a jack is an example of the system (the lever)
4		B	Like you stick it in there or something, pop it open, and then jack it up which raises it.	BS	3	considering the details of how to use a jack
5		B	And then you remove the jack to put it back down.	BS	3	considering the details of how to use a jack
6	16:11	B	Ya, depending on the type of jack.	S	3	considering the details of how a different jack could be used
7		A	Then how do you put it down.	Be	2	considering the interactions between subsystems, (the user and the down movement of the jack)
8		B	Could you just put weights on that? Just like hang weights and it just...	S	3	considering the details of adding weights

Note. Column C are the utterances (what is said) between the two students.

Example B. Freshmen Students

	A	B	C	D	E	F	G
1	Time	Person	Utterance	FBS Code	Systems Level	Coder 1	Coder 2
2		B	Because our device right here,	S	1	1	1
3		B	this clamp,	S	1	1	1
4		B	should be strong enough to hold	Be	1	2	1
5		B	the window up itself.	S	2	2	2
6		B	And then when you want to close it,	Be	2	2	2
7		B	you just got untwist it.	Be	2	2	2

Figure 5. Examples of System Level Coding

The coding was very contextual and therefore required coders to code in the context of what was being discussed. Something that was coded as system level 1 in one utterance does not imply that it remains at system level 1 for the rest of the design

session, nor other design sessions. The coder had to read around the utterances to understand the context and then decide on a code. Consequently, coder disagreements were inevitable and had to be resolved through a coder agreement process. This is discussed in the next section – Coder Agreement.

Coder Agreement

The final systems level code was developed through an arbitration process. This coding scheme allowed a final code to be developed through an agreement of the codes from two coders. Although the arbitrated codes were usually the same as one of the coders, it could also be different from both coders. This coding process can be viewed as a continuous improvement method that allowed the coders to learn and change their codes or opinions over time. Consequently, the code agreement between the coder and the final arbitrated codes increased over time. Two measures of coding validity are used, coder percentage agreement and Cohen's Kappa. The goal was to reach a coder agreement of 80% to be consistent with similar systems level coding (Song, 2014) and FBS coding (Becker et al., 2019). However, a minimum intercoder-reliability of 70% must be maintained to be acceptable for social sciences (Schloss & Smith, 1999). Cohen's Kappa was used to measure the intercoder-reliability between coder 1 and coder 2.

The researcher was coder 1 and two graduate students, who were experienced in FBS coding, volunteered to be coder 2 for some design sessions. Training on systems level coding was provided to the two graduate students. Training materials included a brief literature review on systems coding, Table 3, and examples like Figure 5. The

researcher was coder 2 for the remaining design sessions. This meant that the researcher encoded each design session twice, with at least ten days in between each coding. The ten-day break addresses the issue of coder fixation on the first round of coding and improves independence of each round of coding (Gero & Mc Neill, 1998). Disagreements were self-arbitrated to produce the final system codes, which formed the database for analysis.

The methods and tools used for the analysis in each of the four research question are discussed next.

Research Question 1 - Problem Decomposition and Recomposition

Research Question 1 purports to measure systems thinking between students (novice) and professional engineers (experts) by examining their top-down and bottom-up problem-solving strategy when solving engineering design problems. Consistent with terms used in the literature, a top-down problem-solving strategy is problem decomposition and a bottom-up problem-solving strategy is problem recomposition. The question of interest is: do expert's problem decompose and recompose more than novices? To answer this question, problem decompositions and recompositions of experts and novices were quantitatively measured and compared.

Problem decomposition and recomposition was measured by analyzing the sequential process of system levels 1, 2 and 3. System level O was omitted for this part of the analysis. Sequential means that each systems code is paired with the next code, and these pairs of codes formed the processes of either problem decompositions, problem recompositions, or neither – which meant the designers stayed at the same level. When

the designers went from a higher level to a lower level, for example level 1 to level 3 (in rows 3-4 in Example A of Figure 5), it is a top-down approach and is considered problem decomposition. Conversely, if the designers went from a lower level to a higher level, for example level 3 to level 2 (rows 6-7 in Example A of Figure 5), it is a bottom-up approach and is considered problem recomposition. Problem decomposition and recomposition from the various systems processes are summarized in Table 4.

Table 4

Problem Decomposition and Recomposition

Problem Decomposition/Recomposition	Systems Process
Problem Decomposition	1 → 2, 1 → 3, 2 → 3
Problem Recomposition	2 → 1, 3 → 1, 3 → 2
Same Level	1 → 1, 2 → 2, 3 → 3

To test the hypothesis (H1) in research question 1, percentages of problem decomposition and recomposition were computed in Excel with the aid of macros and other excel built-in functions. Percentages of system levels 1, 2, 3, and O were also computed as a preliminary step to problem decomposition and recomposition. Problem decomposition and recomposition are used interchangeably with systems process throughout the document. The process was repeated for all the sessions and the results were aggregated based on the three cohorts: professional engineers, senior students, and freshmen students. Correspondence analysis, Markov models, descriptive and inferential statistics were tools used to analyze the data. An example of the professional engineers' data is attached in Appendix D.

Correspondence Analysis

Correspondence analysis (CA) (Husson, Lê, & Pagès, 2010) is a form of multivariate analysis. This is suitable when the researcher is interested in studying the relationships of many variables (more than 2). In this research, there are 9 variables of interest, namely, system levels 1, 2, 3, O, problem decomposition, problem recomposition, and the three cohorts; professionals, seniors, and freshmen. The variables are arranged into rows and columns and grouped as categories. For example, systems levels and system processes are the rows and the three cohorts are the columns. The intersection of each row and column is the count or frequency for that category. See Figure 6 below for an example of a correspondence table.

Correspondence Table				
Categories		**Cohort**		
		Professional Engineers	*Senior Students*	*Freshmen Students*
System Levels and System Processes	*Level 1*			
	Level 2			
	Level 3			
	Level O		Count/Frequency	
	Decomposition			
	Recomposition			
	Same Level			

Figure 6. Example Correspondence Table

The result is a table, which has many names, but mean the same thing in CA. Some commonly used names are correspondence table (created using SPSS), pivot-table (created using Excel), contingency table and cross-table. One way to think of CA is to think of each variable as a separate dimension, so for *n* variables, there are *n* dimensions. CA reduces the number of dimensions, *n*, down to 2 because 2D is easier to interpret. The result is a 2D plot that is a qualitative overview of the data. It is qualitative in the sense

that it shows is how similar or dissimilar the variables are with each other by looking at their positions with regards to dimension 1 (x-axis) and dimension 2 (y-axis). For example, if variables A and B sit on the same side of a dimension, there are similarities between A and B. If they sit on the same quadrant, they are categorically similar. In this research, we wanted to know how each cohort (professionals, seniors, freshmen) share similarities within various aspects of systems thinking (systems levels 1, 2, 3, O, problem decomposition and recomposition). Where do professionals sit related to system level 1 to indicate if there are categorical similarities or dissimilarities between professional engineers and thinking at the systems or big picture level? Where do students sit related to system level 3 to indicate if there are categorical similarities or dissimilarities between students and thinking about details of the problem? Where do professionals sit related to problem decompose and recompose compared to engineering students? The results of CA for this study are presented in Chapter 4.

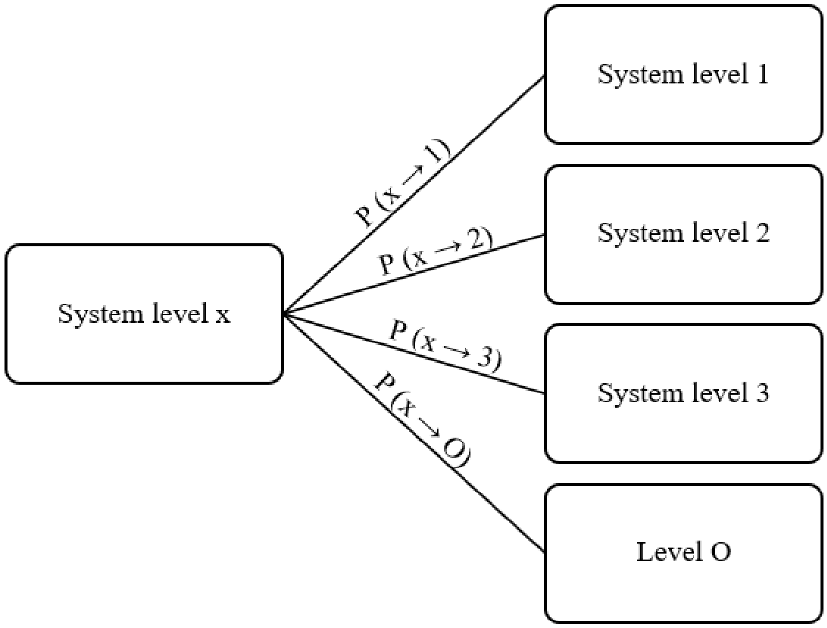
Descriptive and Inferential Statistics

CA was used to provide an overview of the data and pointed to areas of similarities. For a more detailed analysis of system levels and system processes for the three cohorts descriptive and inferential statistics were used. Means and standard deviations were computed and compared across the three cohorts for central tendency and spread of the data. Furthermore, SPSS was used to check for ANOVA assumptions of normality by Shapiro Wilk test, $p \geq 0.05$ and homogeneity of variance by Levene's test, $p \geq 0.05$. If normality was not met, a non-parametric test was used instead, and Kruskal-Wallis p-values are reported. Independent samples were met by design of the experiment because each design team's data was collected independently in the previous study

(Becker et al., 2019). ANOVA was performed on the percentages of system levels, and problem decomposition and recomposition for the three cohorts. A significance level of 0.05 was selected and host-hoc tests were followed up for ANOVA $p \leq 0.05$ to identify where and which cohorts differed. Statistical significance was accompanied by measurements of effect size, specifically, partial eta squared, which measured the strength of the relationship between the variables. A larger effect size implied a stronger relationship and a larger practical significance.

Markov Models

To further understand problem decomposition and recomposition, Markov models (Kan & Gero, 2017) was used to assess and predict the systems processes for each cohort. Markov analysis computes the probabilities of going from one systems level to another systems level, or the probabilities of the systems processes. This is explained with the help of a tree diagram example in Figure 7. In general, the probabilities are obtained by weighing the system process of interest to all possibilities of that system process. For example, what is the probability of going from system level 1 (x = 1) to system level 2 or P (1→2)? We would count all occurrences of 1→2 and divide by the counts of all possibilities: 1→1, 1→2, 1→3, and 1→O or mathematically:
$\mathrm{P}(1 \rightarrow 2) = \sum(1 \rightarrow 2) \, / \sum(1 \rightarrow 1, 1 \rightarrow 2, 1 \rightarrow 3,\ 1 \rightarrow \mathrm{O})$. The result is a value between 0 and 1 which is the probability of going from system level 1 to 2. This was repeated for all other values of x and for the three cohorts. The results were aggregated based on cohorts and their means and standard deviations were computed. Additionally, ANOVA was performed to find statistical significance and effect size was calculated.



Note. P (x → 1) is the probability of system level x going to system level 1, where x = 1, 2, 3, or O.

Figure 7. Probabilities of System Processes

Research Question 2 - FBS and Problem-Solution Space

As illustrated in the literature review, an avenue of interest in design cognition is how designers distribute their cognitive effort in the problem space and solution space (Atman et al., 2007; Becker et al., 2019; Dixon, 2011; Jiang et al., 2014). Research question 2 purports to measure systems thinking of experts and novices in the problem space and solution space. The researcher hypothesizes that systems thinking of experts, specifically system level 1 and problem decomposition, are compelled to the problem space. Comparatively, novices would be compelled to the solution space.

Jiang, Gero, & Yen, (2014) came up with a single value measurement of problem space-solution space for each design session called the Problem-Solution (P-S) Index.

The P-S Index is a ratio of the total occurrences of the FBS design issues concerned with the problem space to the sum of those related to the solution space. Mathematically, this can be expressed as a single equation such as equation (1). Similarly, P-S Index for FBS design processes can be calculated by equation (2).

$$\text{P-S Index (design issue)} = \frac{\sum(\text{Problem}-\text{related issues})}{\sum(\text{Solution}-\text{related issues})} = \frac{\sum(R,F,Be)}{\sum(Bs,S)} \quad (1)$$

$$\text{P-S Index (design process)} = \frac{\sum(\text{Problem}-\text{related issues})}{\sum(\text{Solution}-\text{related issues})} = \frac{\sum Process(1,7,8)}{\sum Process(2,3,4,6)} \quad (2)$$

Recall from Figure 5 that each systems level code had a corresponding FBS code or FBS Issue. The FBS Issues guided the allocation of each systems code to the problem-space or solution-space. Similarly, FBS Processes guided the allocation of each systems process to the problem-space or solution-space. FBS Issues and FBS Processes in the problem-solution space are summarized in Table 5. The result is a separation of system levels and system processes in the problem-space and those in the solution-space.

Table 5

Problem-Solution Space for FBS Issues and Processes

FBS	Problem-Space	Solution-Space
Issues	Requirements (R) Function (F) Expected Behavior (Be)	Behavior from Structure (Bs) Structure (S)
Processes	Formulation (1) Reformulation 2 (7) Reformulation 3 (8)	Synthesis (2) Analysis (3) Evaluation (4) Reformulation 1 (6)

Applying P-S Index equations (1) and (2) to system levels and system processes respectively, we obtained two equations that were used to compute PS-Index for system levels – equation (3) and PS-Index for system processes – equation (4). System levels are summarized in Table 3 and system processes are summarized in Table 4.

$$\text{P-S Index (system level)} = \frac{\sum(\text{Problem}-\text{related issues for the system level})}{\sum(\text{Solution}-\text{related issues for the system level})} \quad (3)$$

$$\text{P-S Index (system process)} = \frac{\sum(\text{Problem}-\text{related issues for the system process})}{\sum(\text{Solution}-\text{related issues for the system process})} \quad (4)$$

P-S Index (system level) – equation (3) measured the ratio of cognitive effort spent in the problem space compared to the solution space for each system level. Similarly, P-S Index (system process) – equation (4) measured the ratio of cognitive effort spent in the problem space compared to the solution space for each system process. Equations (3) and (4) yields P-S Index values between 0 and infinity – theoretically. However, as illustrated from previous studies by Kan and Gero (2017), an upper bound for P-S Index is approximately 1. A negative P-S Index was not possible because the minimum value of the numerators were 0. A P-S Index equal to 1 signals a balance between the problem and solution space. A P-S Index greater than 1 means that more cognitive effort was put into the problem space than the solution space. A lower P-S Index meant that the design team was more solution focused. On the other hand, a higher P-S Index meant the design team was more problem focused. For example, if team A had a P-S Index score of 0.5 for system level 1 and Team B had a score of 0.7, it is concluded that team B spent more cognitive effort in the problem space compared to team A in system level 1.

Using Excel, P-S Index values for system levels and processes were calculated for all the design sessions, and then aggregated across the three cohorts; professional

engineers, senior students, and freshmen students. System processes were grouped into problem decomposition, recomposition, or same level, as guided by Table 4. Means and standard deviations were calculated, and ANOVA was performed to check for statistical significance. If a significance was found in the between group differences, indicated by ANOVA, $p \leq 0.05$, post-hoc tests were followed up to identify which pair of cohorts were statistically different. Systems level 1 was hypothesized in H2 because, based on evidence from the literature review about expert-novice designers, professional engineers (experts) tend to think broader and solve problems from wider perspectives that are higher in the systems hierarchy or system level 1. However, systems level 2, 3, and O were also analysed in the same way to provide a complete analysis.

Research Question 3 - Team Interaction and Problem Decomposition/Recomposition

In practice, teams are essential to solve complex engineering problems (Gyory et al., 2019; Hsu, 2017; Lerdahl, 2001; Oladirana et al., 2011). Therefore, to better understand team interactions of experts and novices when solving complex problems, research question 3 purports to measure and compare team interactions of expert teams and novice teams through the lens of problem decomposition and recomposition. The researcher hypothesized that members of expert teams would interact more than novice teams to achieve problem decomposition. In order to test the hypothesis, a mapping process that measured the simultaneous activity of team interactions and problem decompositions/recompositions was required. This is discussed next.

From FBS coding, each utterance corresponded to either person A or B. Column B of Figure 5 showed which person, A or B, stated the utterance in column C. In example

A of Figure 5, row 7 is said by person A and row 8 is said by person B. Here, an interaction took place because person A is followed by person B (denoted as AB). The reverse, person B followed by person A (BA) is also considered an interaction. Interactions between the same person, for example when person A is followed by A (AA) or when person B is followed by B (BB), are not considered team interactions. Interaction analysis considered the process of communication and turn-taking between two people while designing as a team. As a team interaction took place from segment 7-8 in example A, a system process also took place from system level 2 to 3, which is considered problem decomposition according to Table 4. Therefore, in this example, a team interaction took place where they problem-decomposed, and this is denoted as "Decomposition-Interaction". The alternative is "Recomposition-Interaction", where an interaction between person A and B occurred and the system process was problem-recomposed.

This process was repeated for the entire session and normalized over the total occurrences of problem decompositions for that session. Equations (5) and (6) were used to compute decomposition-interaction and recomposition-interaction respectively.

$$Decomposition - Interaction = \frac{\sum Problem\ Decomposition\ with\ Interaction}{\sum Problem\ Decomposition} \qquad (5)$$

$$Recomposition - Interaction = \frac{\sum Problem\ Recomposition\ with\ Interaction}{\sum Problem\ Recomposition} \qquad (6)$$

One session produced a Decomposition-Interaction value and a Recomposition-Interaction value between 0 and 1. This process was repeated for all sessions and the result were aggregate based on the three cohorts. Means and standard deviations were

computed, and ANOVA was performed. Post-hoc tests were followed up for ANOVA $p \leq 0.05$ to identify which pair of cohorts were statistically different.

Research Question 4 - Personality Traits and Systems Thinking

This exploratory research questions sides with evidence in the literature that a relationship exists between individual personalities and systems thinking. The research question seeks to better understand this relationship through psychological trait theory. In particular, the Big Five was implemented to collect and analyze the personality traits of the participants. However, this came with several limitations.

The existing FBS data was based on a previous NSF project (Becker et al., 2019) that was not experimentally designed to measure personality traits. The research question differed from the previous research questions because it did not compare professionals to students. Instead, it treated all participants as one group and measured systems thinking from a personality trait point of view. The assumption here is that personality traits are independent of the environment and individuals exhibit these traits when solving engineering design problems. The challenge was to go back to the participants, after two years, and ask for their voluntary participation to take a 5-10 minutes survey (attached in Appendix A - see Data Collection section for details on this). The personality traits of the participants were unknown until the data is collected. This implied that the personality information had several limitations. First, we acknowledged that we had insufficient data source (122 participants or 61 teams of two) to cover all possible combinations of personality traits for a team of two individuals. However, we did not expect to cover all trait combinations because recent studies have shown that engineers have about one to

two dominant traits (Cárdenas Moren et al., 2019; Williams, 2009; Williamson et al., 2013). Second, since the design solution was the cumulative work of both individuals, both participants in the team had to complete the survey for the data to be valid for analysis. If only one person or no person in the team took the survey, the session was discarded. The goal was to get as many participants to fill the Big Five Inventory personality survey (Soto & John, 2009) as possible. The details of participant recruitment and incentive are explained in the Data Collection section. The Big Five is discussed next.

Big Five Personality Traits

The Big Five refer to the five personality traits or factors; *Extraversion, Agreeableness, Conscientiousness, Neuroticism,* and *Openness*, that stemmed from an analysis of the English language to better understand personality (Digman, 1990). This was possible because trait theory enabled peoples' temperament to be described by traits or words that describe behavior, for example: friendly, confident, quiet, etc. The wording of the Big Five factors vary slightly and different names have been used to label each factor. Some factors were harder to capture and less obvious than others, nonetheless, there was a consensus to the number of factors - five. The following trait names were adopted from Digman (1990) in his annual review of psychology and will be used for this study:

Extraversion (or Surgency): is associated with being sociable, gregarious, assertive, talkative, and active.

Agreeableness (or Friendliness): is associated with being courteous, flexible, trusting, good natured, cooperative, conforming, forgiving, soft-hearted, and tolerant.

Conscientiousness (or Will): is associated with the will to achieve, dependable, careful, thorough, responsible, organized, planful, hardworking, self-controlled, and persevering.

Neuroticism (or Emotional Stability): is associated with being anxious, depressed, angry, embarrassed, emotional, insecure and worried.

Openness (or Intellect): is associated with being imaginative, cultured, curious, original, broad-minded, intelligent, and artistically sensitive.

The Big Five was well validated across instruments and observers (McCrae & Costa, 1987). In their analysis of 738 peer ratings of 275 adult subjects, intraclass correlations among raters and correlations between mean peer ratings and self-reports showed substantial cross-observer agreement on all five adjective factors. The Big Five was also proven to be consistent in longitudinal studies (Soldz & Vaillant, 1999), where 165 men were followed over a period of 45 years and their trait profiles were found to be relatively stable. Moreover, strong correlations were found for neuroticism, extraversion and openness over the 45-year period. Although the Big Five is a popular tool among educational and psychological researchers, it has limitations because it is a form of self-report to measure psychological constructs. Mcdonald (2008) pointed out that such an instrument is prone to response bias because people often respond in a way that presents them in a more favorable light, even if the response does not reflect how they actually think or behave. Other weaknesses include poorly structured questions that do not accurately measure the construct under consideration, and acquiescence responding, in

which individuals respond without considering what the question is actually asking. The instrument used in this study (details in Data Collection section) was developed by Soto & John (2009). The authors have carefully structured the questions to measure what it is intended to measure and addresses acquiescence in their algorithm to compute trait scores.

The alternative to the Big Five is the Myers-Briggs Type Indicator (MBTI). To some extent, the MBTI is popular among educational research and clinical practice because it is an expedient and convenient way to assess one's personality. However, critics have questioned the validity of MBTI and its applications (McCrae & Costa, 1989). MBTI is a type indicator rather than a trait. It assumes that an individual can by classified into 1 of 16 personality types formed by 4 dichotomous preferences. Each type is discrete in the sense that you are either it or not (1 or 0) and nothing in between. On the other hand, the Big Five bases each factor on a scale of 0 to 100. The continuous variables provide better predictive power over MBTI. Furthermore, the Big Five provides a richer pool of information because it considers personality from five factors of preferences as compared to four for the MBTI. Jungians and personality psychologists question the validity of MBTI as they claim that Jungian concepts, which MBTI is supposed to underlie, have been distorted (McCrae & Costa, 1989).

Survey Instrument – Big Five Inventory

The chosen instrument is the Big Five Inventory (BFI) personality survey, which is a set of 44 questions, Appendix A (Soto & John, 2009), that has been simplified from the widely used Neuroticism, Extraversion, Openness Personality Inventory Revised (NEO-PI-R) (P. T. Costa & McCrae, 1992). BFI is found to converge with facets

assessed by NEO-PI-R (Soto & John, 2009). Although BFI is a shortened version of the NEO-PI-R, it provided a sufficient level of information that captured the personality traits of the participants. BFI asks participants to self-evaluate to a 5-point scale, where 1 = disagree strongly and 5 = agree strongly.

Teams where both members completed the BFI survey (complete teams) were considered for the analysis. Incomplete surveys and teams where only one person or no person completed the survey were discard and was not considered in the analysis. In cases where the participants completed the survey multiple times, the latest survey response was recorded, and the earlier versions were discarded.

Participant responses were scored based on the algorithm described in Appendix B (Soto & John, 2009). The score for each factor or trait took an average of all items that are associated with that factor. A reverse-score system was implemented to adjust for acquiescence. Raw scores were standardized using a comparison sample, which consisted of 71,867 participants (54% female) between the ages of 21 and 60. All selected participants lived in the United States with 9.2% of the sample from Canada (Srivastava, John, Gosling, & Potter, 2003). For the complete teams, average team trait score for each of the five traits were computed. Although team averaging has limitations, it is a common method that is used in team personality trait studies (Barrick et al., 1998; Mohammed & Angell, 2003; Reilly et al., 2002; Toh & Miller, 2016). The team scores are percentile scores ranging from 0 to 100 on each of the five factors (Extraversion, Agreeableness, Conscientiousness, Neuroticism/Emotional, Openness).

The analysis of personality traits and systems thinking consisted of two steps. First, participants were grouped into students and professionals. Their individual

personality trait scores were aggregated according to the groups and compared to the comparison sample based in the U.S. and Canada. This provided a comparison for the personality traits of engineers (students and professionals) to that of the population in the U.S. and Canada. Second, relationships between team trait scores and systems thinking were explored using correspondence analysis (CA) (Husson et al., 2010), correlation, and analysis of covariance (ANCOVA). SPSS was used for the analyses. Here, professional and student teams were combined into one group with N teams. Results of CA were used to identify categorical similarities or differences between systems thinking and team personality traits. This produced a qualitative representation of the data because categorical similarities are measured by how close (or far if dissimilar) the traits are in relation to the system levels (1, 2, 3, and O) and system processes (problem decomposition, problem recomposition, and same level). Each personality trait was correlated with system levels and system processes. Pearson correlation with a significance level of 0.05 was used to identify significant correlations. ANCOVA was employed with personality traits being the independent variable, systems levels and processes being the dependent variable, and design experience being the covariate. The covariate controlled for differences in professional and student design experience.

Participants:

The participants consisted of professional engineers and undergraduate engineering students (seniors and freshmen) that previously took part in an NSF funded study; Grant No. EEC-1463809 and EEC-1463873. There were 61 teams, and each team consisted of two members; therefore, a total of 122 participants were involved in this study. There were 43 teams of undergraduate engineering students (19 seniors and 24

freshmen) from Utah State University who majored in mechanical, civil and environmental, and biological engineering. Freshmen were engineering students enrolled in year-one or freshmen engineering courses. Seniors were engineering students enrolled in year-four or senior engineering courses. There were 18 teams of professional engineers. To be considered ‘professional’, engineers had to have at least 10 years of work experience. Professional Engineering licensure was not required. The engineers spanned across the States of Utah, California, and Washington with a majority (75%) from Utah.

Institutional Review Board (IRB)

The participants had participated in the aforementioned NSF project between 2017 and 2018; therefore, an IRB already existed. This study was considered a continuation and was exempt from IRB review. Additionally, a Letter of Information was issued to participants that informed them about the follow-up study and provided a rationale for their time to fill out the Big Five personality survey.

Data Collection

The only data that was collected was the personality survey guided by the Big Five Inventory (BFI) (Soto & John, 2009). The BFI survey was set up in Utah State University (USU) Qualtrics and then distributed to the participants. USU Qualtrics was selected because it was compliant with university research standards and ensured confidentiality and privacy. Moreover, USU Qualtrics was easy to use and accessible on different devices (PC, mobile, tablet etc.) with internet access. A survey link was generated and included in the email to the participants. The email was sent in conjunction

with the result of the aforementioned NSF project, which the participants expected as they were informed at the conclusion of their research sessions. The email was titled “Results and Request” so that participants were aware that in addition to the results, a follow up survey, related to the previous research work, was requested. The survey consisted of 45 questions where the participant had to self-evaluate on a 5-point scale (1 = Disagree strongly and 5 = Agree strongly) and would take approximately 5-10 minutes to complete. Participation in the survey was complete voluntary and participants were encouraged to participate with a $10 Amazon gift card as an incentive.

The email was sent three times, after which no more follow-up emails were sent to the participants. The time gap between each email was approximately two weeks. The first email was sent to all (122) participants. The second email was a reminder to the remaining participants who had not taken the survey and did not respond. The final email was a nudge to team members whose teammates had already taken the survey. This was necessary for several reasons: 1) there was a two-year gap between this study and the previous study where the participants were involved, 2) senior students have graduated and professional engineers may have changed jobs; therefore, their emails may have changed, became redundant, or even forgotten, and 3) to maximize participation given our low numbers.

CHAPTER IV

RESULTS

This study investigated systems thinking of expert and novice design teams. Eighteen teams of professional engineers form the expert cohort, and 19 teams of seniors and 24 teams of freshmen form the two novice cohorts. Using the methodology described in Chapter III, systems thinking of experts and novices were measured and compared quantitatively. To solicit differences in expert and novice, Function-Behavior-Structure (FBS) tools developed in earlier studies (Kan & Gero, 2017) were employed to investigate systems thinking and interrelated areas such as problem-space / solution-space focus and team interactions. Additionally, personality traits were explored to unveil relationships of personality and systems thinking. The results were based on 61 design team's verbal protocol data (18 professionals, 19 seniors, and 24 freshmen), which were collected and coded using FBS in a previous study (Becker et al., 2019).

Pre-coded FBS data for 61 design sessions underwent systems hierarchical coding. Two coders coded each session and arbitrated any disagreements to reach the final systems hierarchical codes. The average agreement between the two coders was 80% and an intercoder reliability, measured by Cohen's kappa (k), was 0.78. The results from the hierarchical coding produced 61 sessions worth of data, where every utterance or FBS segment in each session was coded into either systems level 1, 2, 3, or O. This formed the basis for quantitative analysis, and Statistical Package for the Social Sciences (SPSS) was the software package used for the analysis.

Distributions of System Levels and Problem Decomposition/Recomposition provide an overview of systems thinking between the three cohorts: professionals,

seniors, and freshmen. Additional analysis was carried out to address each research question. Markov models were implemented to investigate the probabilities of problem decomposition and recomposition of experts and novices in Research Question 1. FBS Problem-Solution (P-S) Index analysis was applied to systems thinking in Research Question 2 and team interaction analysis was done for Research Question 3. Exploratory Research Question 4 combined three sets of data; system levels (level 1, 2, 3), system processes (problem decomposition/recomposition), and personality traits (extraversion, agreeableness, conscientiousness, neuroticism, openness) to solicit relationships through correspondence analysis, correlation, and analysis of covariance (ANCOVA).

Analysis of Variance (ANOVA) was run on the data to answer research question's 1-3. The pre-requisites for ANOVA are independent samples, normality, and homogeneity of variance of the data. Verbal protocol data for each design team was collected using independent samples (Becker et al., 2019). The data is assumed normal by Shapiro-Wilk $p > 0.05$, and variance is assumed homogeneous by Leven's $p > 0.05$. In situations where normality was *not* satisfied, the author addressed it with non-parametric tests such as Kruskal-Wallis and Mann-Whitney. If homogeneity of variance was not met, ANOVA was run assuming unequal variances. If a significant difference was found between the cohorts, indicated by $p < 0.05$, a post-hoc analysis was used to identify which cohorts differed. Figure 8 provides a graphical illustration of the data flow and analysis that guided this chapter.

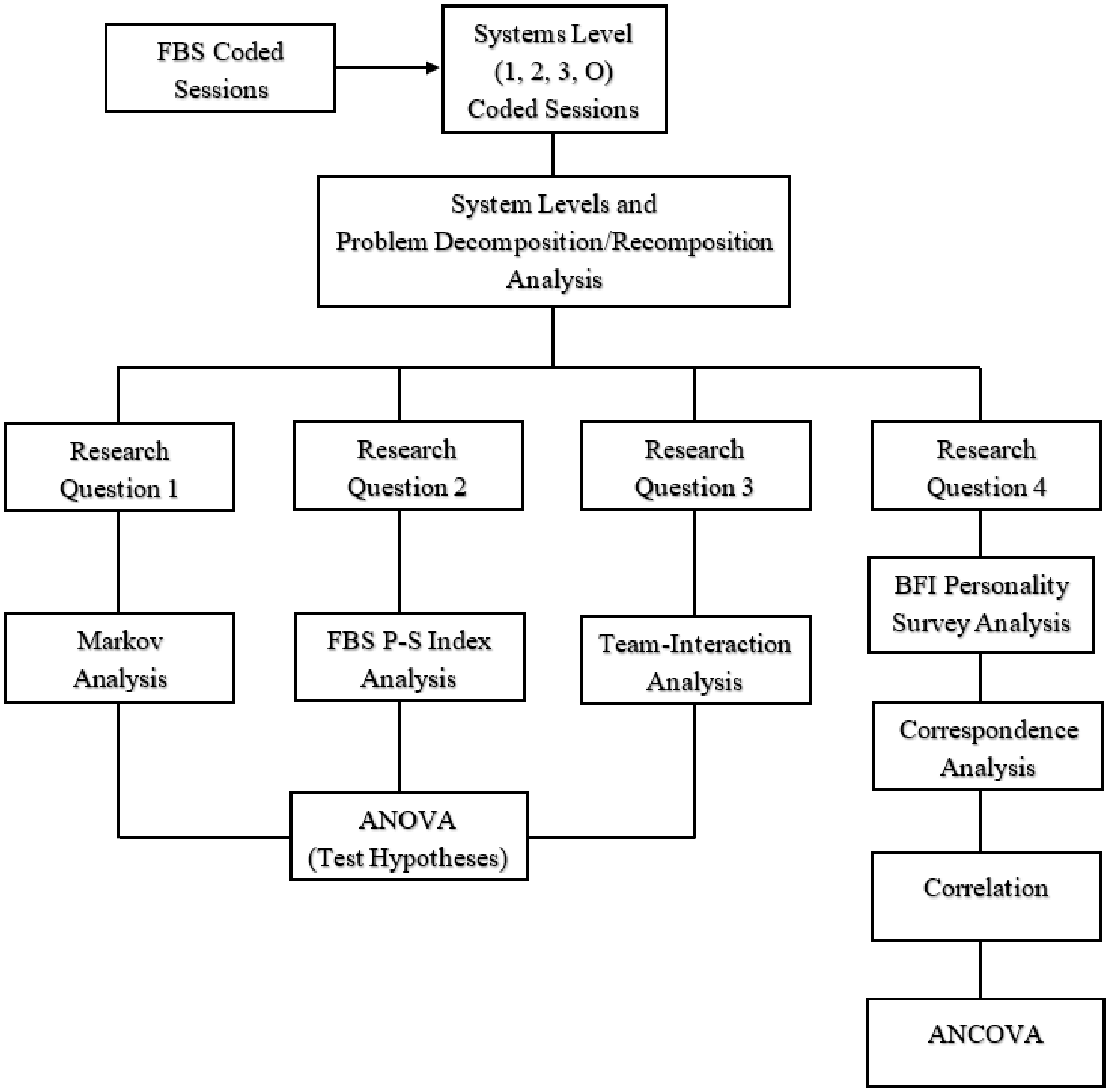


Figure 8. Dataflow for Analysis

To provide an overview of the data, correspondence analysis (CA) brought together the system levels (level 1, 2, 3, O), system processes (problem decomposition, recomposition, same level), and the three cohorts (professionals, seniors, freshmen) into a single 2D plot – see Figure 9. Systems thinking refer to the system levels and system processes, which are shown by red circles in Figure 9. The three cohorts are represented by blue circles. System levels, system processes, and the cohorts are treated as categorical

data. A total of 10 categories are presented in Figure 9. Dimension 1 covers 95.6% of the variance of the data and dimension 2 covers 4.4% of the variance of the data; they add up to cover 100% of the variance of the data.

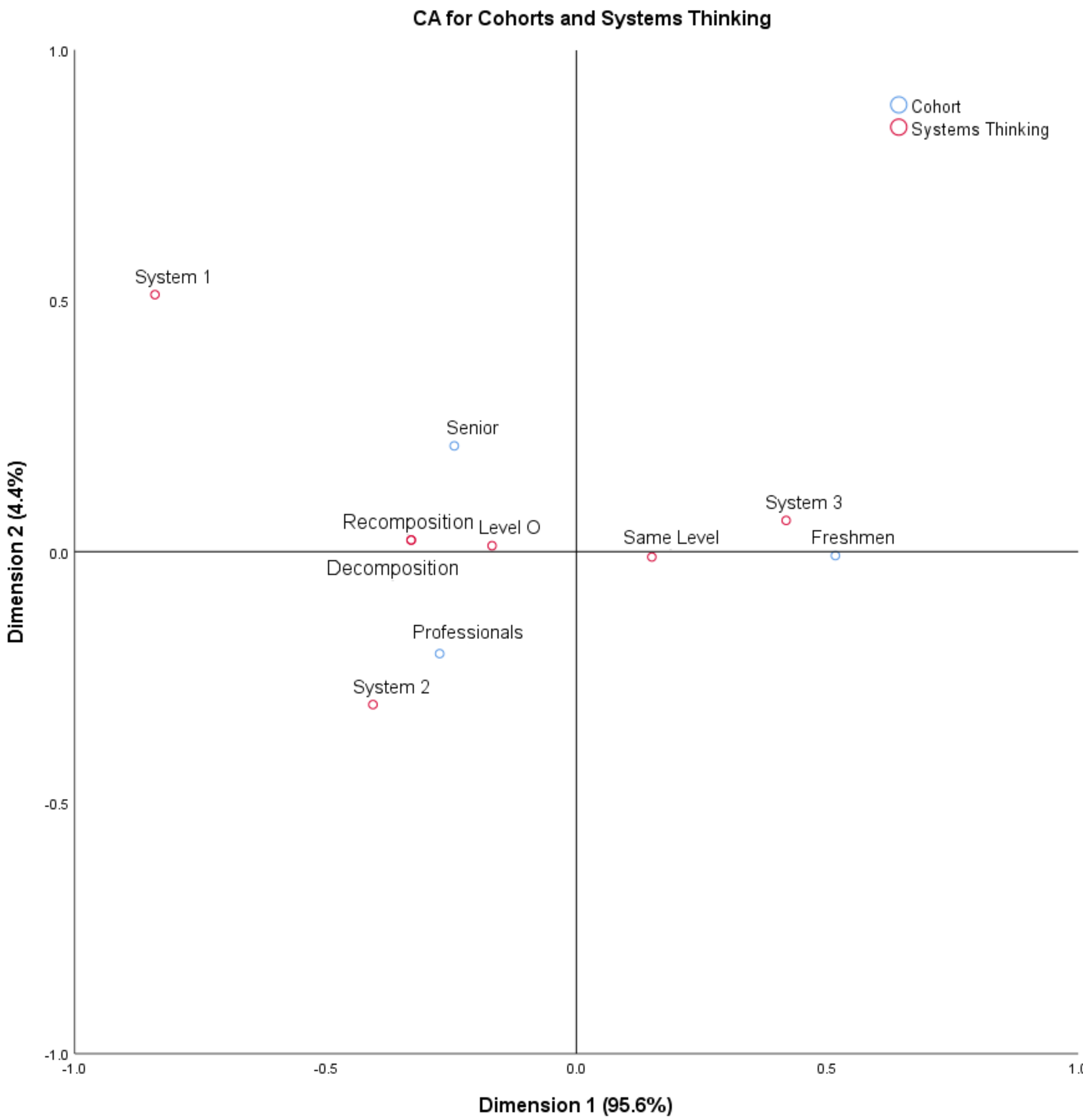


Figure 9. Correspondence Analysis for Cohorts and Systems Thinking

CA plots the categories in a 2D space to indicate categories that are similar. Categorical similarities are determined by categories that are in the same quadrant, for

example in Figure 9, professionals and system level 2 are in the same quadrant compared to senior or freshmen and system level 2, therefore, professionals and system level 2 are categorically similar. Since dimension 2 only covered 4.4% of the variance of the data, much of the variance of the data is covered in dimension 1. Freshmen, same level, and system level 3 sit on the positive side of dimension 1, therefore they are categorically close to each other. The same can be said for the categories on the negative side of dimension 1. There are three ways to identify categorical similarities and differences: 1) left and right of dimension 1, which covers a majority of the variance of the data (95.6%), 2) top and bottom of dimension 2, which covers 4.4% of the variance of the data, and 3) a combination of dimension 1 and 2, which are the four quadrants.

An overview of the data can be determined by looking at the quadrants. From Figure 9, system level 1, 2, and 3 sit in different quadrants, which suggest that they are categorically different from each other. Similarly, the three cohorts: professionals, seniors and freshmen, sit in different quadrants, which suggest that they are categorically different. On the contrary, decomposition and recomposition sit in the same quadrant, in fact, the circles are right on top of each other, which suggest that they are categorically very similar. Senior students sit in the same quadrant as system level 1, system level O, decomposition, and recomposition, which suggest categorical similarities. The same can be said for professionals and system level 2, and Freshmen and same level. The categorical similarity of the latter is mostly explained by dimension 1, because there is a horizontal distance, rather than dimension 2, because there was minimal vertical distance between the two categories. To better understand the categorical similarities, descriptive and inferential statistics are discussed next.

For the remainder of this chapter, the results are presented and organized in order of the research questions and their accompanying hypotheses.

Research Questions:

1. What are the differences in systems thinking between professional engineers and engineering students when solving engineering design problems?

   H1: Professional engineers will use problem decomposition and recomposition more than engineering students.

2. What are the differences in systems cognitive effort between professional engineers and engineering students related to FBS problem space and solution space?

   H2: Professional engineers will have more systems level 1 in the "FBS Issues" problem space than engineering students.

   H3: Professional engineers will have more problem decomposition in the "FBS Processes" problem space than engineering students.

3. How do team member interactions affect problem decomposition and recomposition?

   H4: Professional engineers will use problem decomposition more as team interactions increase compared to engineering students.

4. What is the relationship between the Big Five personality traits and systems thinking in engineering design?

Research Question 1

Systems hierarchical coding produced a list of systems codes, which consisted of levels 1s, 2s, 3s and Os for each session. Each session is normalized by talking a ratio of the system level (1, 2, 3, or O) over the total system levels. This can be multiplied by 100 to obtain the percentages. System levels for each session are grouped then aggregated by professionals, seniors, and freshmen. The results for the means (M), standard deviations (sd), and ANOVA are summarized in Table 6.

Table 6

Results for System Levels

System Levels	**Level 1**		**Level 2**		**Level 3**		**Level O**	
Cohort (M, SD)	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Professionals (N = 18)	0.12	0.05	0.34	0.08	0.46	0.12	0.08	0.03
Seniors (N = 19)	0.14	0.06	0.30	0.08	0.48	0.10	0.08	0.03
Freshmen (N = 24)	0.06	0.03	0.23	0.06	0.64	0.08	0.06	0.02
ANOVA (p-Values)	0.000**		0.000**		0.000**		0.052	
Post-Hoc Test (p-Values)								
Professionals vs Seniors	0.679		0.264		0.845		0.965	
Professionals vs Freshmen	0.001**		0.000**		0.000**		0.135	
Seniors vs Freshmen	0.001**		0.006**		0.000**		0.071	
Effect Size (Partial Eta Squared)	0.336		0.300		0.432		0.097	

*$p \leq 0.05$
**$p \leq 0.01$
M = mean, *SD* = standard deviation

The means and standard deviations in Table 6 show that on average, senior students are the highest for Level 1 at 14% with a 6% standard deviation. Professional

engineers are the highest for Level 2 at 34% with an 8% standard deviation, and freshmen students are the highest for Level 3 at 64% with an 8% standard deviation. All three cohorts were similar for Level O.

ANOVA was done for system levels to test for significant differences between the cohorts. A *p*-value less than or equal to 0.05 is considered statistically significant and post-hoc tests are followed-up to identify which cohorts differed. The effect size, measured by partial eta squared, was also computed to observe practical significance or how important the differences were. ANOVA results for system levels 1, 2, and 3 in Table 6 are statistically significant with $p < 0.001$. Post-hoc tests showed that professional engineers and senior students have no statistically significant differences across system levels 1, 2, and 3. However, professional engineers and freshmen students are significantly different for the three system levels. Similarly, senior and freshmen students are significantly different for the three system levels. The effect size for system levels 1, 2, and 3 ranged from 0.3 – 0.4, which is considered large. No statistically significant differences were found for system level O.

System levels are further analyzed for problem decomposition and recomposition by their systems process. A system process describes the transitions between one systems level to the next system level. A transition from a higher level to a lower level is decomposition, and the reverse, a transition from a lower level to a higher level, is recomposition. Refer to Table 4 for details of each systems process. The results for the means, standard deviations, and ANOVA for systems process are summarized in Table 7.

Table 7

Results for System Processes

System Processes	**Problem Decomposition**		**Problem Recomposition**		**Same Level**	
Cohort (M, SD)	*M*	*SD*	*M*	*SD*	*M*	*SD*
Professionals	0.17	0.03	0.17	0.03	0.66	0.07
Seniors	0.17	0.03	0.17	0.03	0.66	0.07
Freshmen	0.13	0.03	0.13	0.03	0.73	0.06
ANOVA (p-Values)	0.000**		0.001**		0.000**	
Post-Hoc Test (p-Values)						
Professionals vs Seniors	0.995		0.987		1.000	
Professionals vs Freshmen	0.001**		0.006**		0.003**	
Seniors vs Freshmen	0.002**		0.005**		0.002**	
Effect Size (Partial Eta Squared)	0.246		0.217		0.232	

*$p \leq 0.05$
**$p \leq 0.01$
M = mean, *SD* = standard deviation

The means and standard deviations in Table 7 show that on average, professional engineers and senior students were the same for both problem decomposition and recomposition at 17% with a 3% standard deviation, while freshmen students were at 13% with a 3% standard deviation. Senior and freshmen students were the same for systems process at the same level at 66% with a 7% standard deviation, while professional engineers were at 73% with a 6% standard deviation. Problem decomposition and recomposition constitute 13-17% of system processes or 26-34% combined, whereas same level constitutes 66-73% of system processes.

ANOVA results showed that statistically significant differences were found between the cohorts for all three system processes; problem decomposition, problem recomposition, and same level. In fact, the results were very significant with $p < 0.001$. Post-hoc tests indicate that professional engineers and senior students have no statistically significant differences across all system processes. Professional engineers and freshmen students are significantly different for all system processes. Senior vs freshmen students are significantly different for all system processes. The effect size for system processes were between 0.22 and 0.25, which is considered to have a large effect.

To identify where professionals and freshmen students differed in problem decomposition and recomposition, a Markov model was employed. A Markov model shows the probability of each problem decomposition or recomposition. In other words, if the designer is in system level x, what is the probability of going to system level y? Where x and y are O, 1, 2 or 3. Suppose x = 1, then the possibilities for y are 1, 2, 3 and O. The sum of the probabilities, $p(1 \rightarrow 1) + p(1 \rightarrow 2) + p(1 \rightarrow 3) + p(1 \rightarrow O)$, must equal 1.

The results for the means, standard deviations, and ANOVA for the Markov models are the aggregates of the individual sessions and are summarized in Table 8.

Table 8

Results for Markov Models

System Processes	**Problem Decomposition**						**Problem Recomposition**						**Same Level**					
	1→2		**1→3**		**2→3**		**2→1**		**3→1**		**3→2**		**1→1**		**2→2**		**3→3**	
Cohort (M, SD)	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Professional	0.22	0.06	0.19	0.07	0.25	0.05	0.10	0.04	0.04	0.02	0.21	0.10	0.43	0.09	0.58	0.04	0.69	0.11
Seniors	0.22	0.07	0.23	0.11	0.26	0.09	0.11	0.04	0.06	0.03	0.17	0.06	0.40	0.11	0.56	0.08	0.71	0.08
Freshmen	0.22	0.07	0.28	0.07	0.36	0.06	0.07	0.03	0.03	0.02	0.13	0.04	0.38	0.08	0.52	0.06	0.79	0.06
ANOVA (p-Value)	1.000						0.001**						0.222		0.005**		0.001**	
Kruskal-Wallis (p-Values)			0.001**		0.000**				0.000**		0.005**							
Post-Hoc Test (p-Values)																		
Professionals vs Seniors			0.283		0.927		0.476		0.063		0.276				0.547		0.848	
Professionals vs Freshmen			0.000**		0.000**		0.029*		0.050*		0.002**				0.005**		0.001**	
Seniors vs Freshmen			0.009**		0.000**		0.001**		0.000**		0.040*				0.075		0.007**	
Effect Size (Partial Eta Squared)			0.176		0.364		0.221		0.269		0.202				0.168		0.224	

*$p \leq 0.05$, **$p \leq 0.01$, *M* = mean, SD = standard deviation.

The means and standard deviations from Table 8 are the probabilities of the systems process. For example, in the first-row professionals have a 19% chance, with a 7% standard deviation, to go from system level 1 to 3 (1→3). This also implies that there is an 81% chance (100% – 19%) that professionals go from level 1 to level 1, 2, or O. Seniors have a 23% chance to go from systems level 1 to 3 and freshmen have the highest chance at 28%. The rest of the table can be interpreted in a similar manner. Problem decompositions 1→3, 2→3, recompositions 2→1, 3→1, 3→2, and same level 2→2, 3→3 were found to be very statistically significant. No statistically significant differences were found for decomposition 1→2 and same level 1→1. The effect size for the Markov models ranged from 0.17 to 0.36, which is considered a large effect.

Research Question 2

The FBS Problem-Solution (P-S) Index was computed for every design session. P-S Index can be computed in two ways, FBS Issues and FBS Processes, and are guided by Equations (1) and (2) respectively:

$$\text{P-S Index (design issue)} = \frac{\sum(\text{Problem−related issues})}{\sum(\text{Solution−related issues})} = \frac{\sum(R,F,Be)}{\sum(Bs,S)} \tag{1}$$

$$\text{P-S Index (design process)} = \frac{\sum(\text{Problem−related issues})}{\sum(\text{Solution−related issues})} = \frac{\sum Process(1,7,8)}{\sum Process(2,3,4,6)} \tag{2}$$

The details of FBS Issues and Processes are in Tables 1 and 2 respectively and they are summarized here. FBS Issues include: Requirements (R), Functions (F), Expected Behavior (Be), Behavior from Structure (Bs), and Structure (S). FBS Processes include: Formulation (1) - which is going from R→F and F→Be, Synthesis (2) - Be→S, Analysis

(3) – S→Bs, Evaluation (4) - Be→Bs and Bs→Be, Documentation (5) - S→D, Reformulation 1 (6) - S→S, Reformulation 2 (7) - S→Be, and Reformulation 3 (8) - S→ F.

Distributions of P-S Index for each system level and systems process indicate the focus of the cohort's cognitive efforts in the problem space and solution space. The means, standard deviations, and ANOVA results for P-S Index for system levels and system processes are summarized in Table 9 and 10 respectively.

Table 9

ANOVA Results for P-S Index for System Levels (FBS Issues)

P-S Index for System Levels	**PS-Level 1**		**PS-Level 2**		**PS-Level 3**		**PS-Level O**	
Cohort (M, SD)	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Professionals (N = 18)	0.50	0.20	0.49	0.15	0.15	0.05	0.41	0.34
Seniors (N = 19)	0.33	0.16	0.45	0.16	0.14	0.05	0.22	0.21
Freshmen (N = 24)	0.35	0.13	0.51	0.19	0.10	0.03	0.23	0.16
ANOVA (p-Value)					0.001**			
Kruskal-Wallis (p-Values)	0.006**		0.515				0.044*	
Post-Hoc Test (p-Values)								
Professionals vs Seniors	0.008**				0.943		0.057	
Professionals vs Freshmen	0.029*				0.004**		0.138	
Seniors vs Freshmen	1.000				0.008**		1.000	
Effect Size (Partial Eta Squared)	0.176				0.203		0.116	

*$p \leq 0.05$
**$p \leq 0.01$
M = mean, *SD* = standard deviation

The P-S Index for system levels in Table 9 indicate that on average for system level 1, professional engineers have a P-S Index of 0.5, with a standard deviation of 0.2, whereas seniors and freshmen students are 0.33 and 0.35 with standard deviations of 0.16 and 0.13 respectively. P-S Index for system level 2 for professionals and freshmen were 0.49 and 0.51 with standard deviations of 0.15 and 0.19 respectively, whereas seniors were 0.45 with a standard deviation of 0.16. P-S Index for system level 3 for professional engineers were 0.15 with a standard deviation of 0.05, seniors were 0.14 with a standard deviation of 0.05, and freshmen were 0.10 with a standard deviation of 0.03. P-S Index for level O for professionals was the 0.41% with a standard deviation of 0.31, whereas seniors and freshmen were 0.22 and 0.23 with standard deviations of 0.21 and 0.16 respectively.

ANOVA is done to compare the means for P-S levels between the three cohorts. Two values are reported, ANOVA p-value and Kruskal-Wallis *p*-values (See Table 9). Kruskal Wallis is a non-parametric test that was run on data that did not meet the normality criteria, where Shapiro-Wilk *p*-value was found to be less than 0.05, which in this case are P-S levels 1, 2 and O. PS level 1, 3, and O are statistically significant different, and no difference was found for PS level 2. Post-hoc tests indicate that professionals are significantly different from both seniors and freshmen students in P-S level 1. Significant differences were also found in PS level 3 between freshmen to both professionals and seniors. No statistically significant differences were found for P-S level O. The effect size for PS level 1 and 3 are 0.18 and 0.20 respectively, which are considered to have a large effect.

A similar process was done for P-S Index for system process (see Table 10). On average, professional engineers have a PS-decomposition of 0.14 with a standard deviation of 0.04, whereas seniors and freshmen were 0.1 and 0.09 with standard deviations of 0.04 and 0.05 respectively. PS-recomposition for professionals was 0.38 with a standard deviation of 0.14, whereas seniors and freshmen were 0.29 and 0.39 with standard deviations of 0.12 and 0.14 respectively. PS-same level for professionals was 0.15 with a standard deviation of 0.04, whereas seniors and freshmen were 0.12 and 0.14 with standard deviations of 0.03.

Table 10

ANOVA Results for P-S Index for System Process (FBS Process)

P-S Index for System Process	**PS-Decomposition**		**PS-Recomposition**		**PS-Same Level**	
Cohort (M, SD)	*M*	*SD*	*M*	*SD*	*M*	*SD*
Professionals (N = 18)	0.14	0.04	0.38	0.14	0.15	0.04
Seniors (N = 19)	0.10	0.04	0.29	0.12	0.12	0.03
Freshmen (N = 24)	0.09	0.05	0.39	0.14	0.09	0.03
ANOVA (p-Value)			0.041*		0.000**	
Kruskal-Wallis (p-Values)	0.001**					
Post-Hoc Test (p-Values)						
Professionals vs Seniors	0.020*		0.106		0.028*	
Professionals vs Freshmen	0.001**		0.976		0.000**	
Seniors vs Freshmen	1.000		0.047*		0.051	
Effect Size (Partial Eta Squared)	0.194		0.105		0.313	

*$p \leq 0.05$
**$p \leq 0.01$
M = mean, *SD* = standard deviation

ANOVA results indicate that there are significant differences between the three cohorts for all P-S Index for systems process. PS-decomposition and PS-same level were very significantly different with $p < 0.01$. Kruskal-Wallis *p*-value was reported for PS-decomposition because the data failed to me normality assumption. Post-hoc tests showed that professionals are significantly different from both seniors and freshmen in PS-decomposition. Seniors and freshmen were different in PS-recomposition. Professionals vs seniors and freshmen were significantly different in PS-same level, but seniors and freshmen were almost significantly different.

Research Question 3

Team interaction analysis was done on each session, where the sequence of speaker (person A or B) turn-taking was mapped onto the corresponding system process. The system processes provide the content for the team interactions. Systems process is either a decomposition (moving from a higher level to a lower level) or recomposition (moving from a lower level to a higher level). Doing so resulted in a list of combinations of person A's and person B's utterances; AA, AB, BA, BB that described the interaction that took place during the system process. The results are aggregated for all the sessions and summarized in Table 11.

Table 11

ANOVA results for Interaction Analysis

Interaction Analysis	**Decomposition-Interaction**		**Recomposition-Interaction**		**Same Level - Interaction**	
Cohort (M, SD)	*M*	*SD*	*M*	*SD*	*M*	*SD*
Professionals (N = 18)	0.17	0.07	0.23	0.09	0.13	0.04
Seniors (N = 19)	0.23	0.08	0.28	0.05	0.19	0.05
Freshmen (N = 24)	0.23	0.07	0.22	0.07	0.15	0.05
Kruskal-Wallis (p-Values)	0.026*		0.049*		0.014*	
Post-Hoc Test (p-Values)						
Professionals vs Seniors	0.032*		0.031*		0.011*	
Professionals vs Freshmen	0.011*		0.861		0.712	
Seniors vs Freshmen	0.777		0.033*		0.173	
Effect Size (Partial Eta Squared)	0.115		0.095		0.172	

*$p \leq 0.05$
**$p \leq 0.01$
M = mean, *SD* = standard deviation

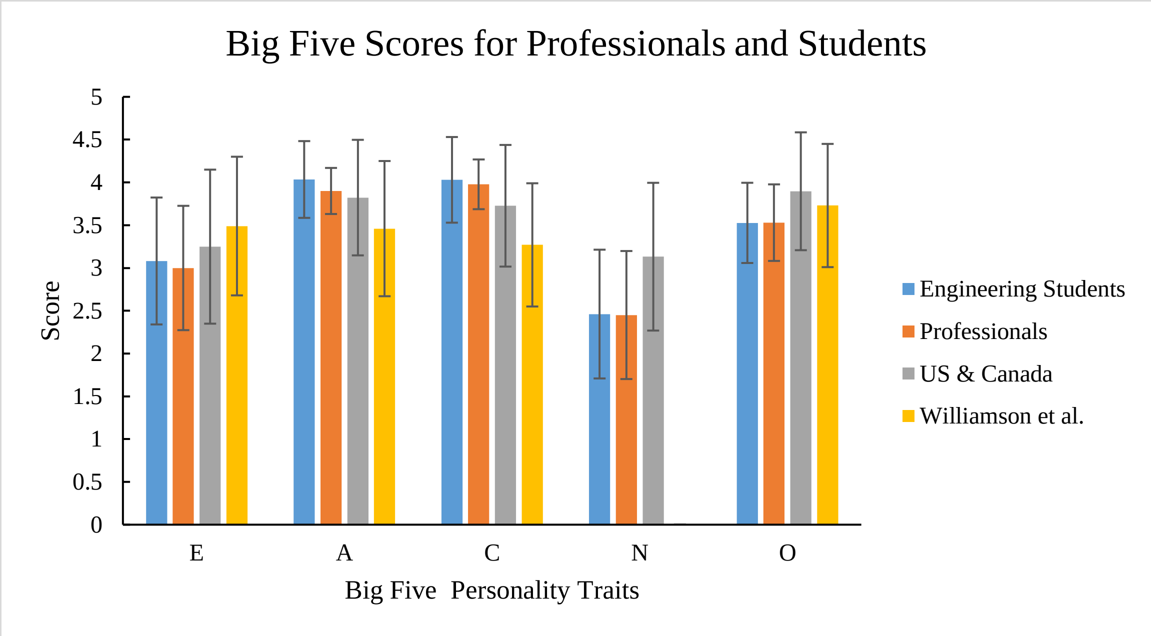
On average, decomposition-interaction for seniors and freshmen were 0.23 with standard deviations of 0.08 and 0.07 respectively, whereas professionals were 0.17 with a standard deviation of 0.07. For recomposition-interaction, professionals were 0.23 with a standard deviation of 0.09, seniors were 0.28 with a standard deviation of 0.05, and freshmen were 0.22 with standard deviations of 0.07. For same level-interaction, professionals were 0.13 with a standard deviation of 0.04, seniors were 0.19 with a standard deviation of 0.05, and freshmen were 0.15 with standard deviations of 0.05. The data sets did not satisfy normality assumptions, therefore Kurskal-Wallis *p*-values were reported. Results showed that there are statistically significant differences between the

cohorts in all three interactions. Post-hoc tests showed that professionals were significantly different from both seniors and freshmen in decomposition-interactions. No differences were found between the students in decomposition-interaction. Seniors were significantly different from both professionals and seniors in recomposition-interactions. No differences were found between professionals and freshmen in recomposition-interactions. Professionals were significantly different from seniors in same level-interaction and no significant differences were found for freshmen with seniors and professionals. The effect size ranged from 0.10 to 0.17, which is considered to have a medium to large effect.

Research Question 4

Research question 4 explored the relationship between personality traits and systems thinking via correlation and ANCOVA. Correspondence Analysis (CA) was not included in the results due to lack of data. Participants were invited to complete the Big Five Inventory (Appendix A) survey online in order to capture the personality profiles of the participants. Eighteen out of 61 teams completed the survey, therefore, the analysis of personality traits only consisted of the 18 teams. There were 5 professional teams and 13 student teams, which total to 36 participants because they worked in teams of two (N=18 teams, n=36 persons). The personality trait scores for the 36 participants were grouped by professionals and students and then aggregated to produce the average scores for each personality trait. The scores are plotted in Figure 10 with two comparison samples, U.S. & Canada and Williamson et al. (2013). U.S. & Canada comparison sample consisted of 71,867 participants (54% female) between the ages of 21 and 60. Williamson et al. (2013) comparison sample consisted of 4876 engineers (18% female) between the ages of

30 and 50 and over. Neuroticism (N) was not included for Williamson et al. (2013) because they measured ‘Emotional Stability’ instead of N. The two are inversely related and therefore not the same.



E = Extraversion, A = Agreeableness, C = Conscientiousness, N = Neuroticism, and O = Openness.

Figure 10. Big Five Scores for Professionals and Students

Figure 10 shows that personality profiles of the participants in this study, professionals and students, were similar in all five traits. Students were higher in Extraversion (E), Agreeableness (A), and Conscientiousness (C) than professionals. Overall, professionals and students were lower in Extraversion, Neuroticism, and Openness than the comparison sample(s). Neuroticism was much lower than Extraversion and Openness comparatively. On the other hand, they scored higher in Agreeableness and Conscientiousness than the comparison samples. Professionals have lower Extraversion and Openness than the engineers in Williamson et al. (2013) but are higher in Agreeableness and Conscientiousness comparatively.

The relationship between personality traits and systems thinking was explored via correlation and ANCOVA. Correspondence Analysis (CA) was not carried out because of a limited sample size. Future studies that seek to include CA in their analysis should include a larger sample size. The idea behind CA was to treat system levels (level 1, 2, 3, O), system processes (problem decomposition, recomposition, same level), and personality traits (Agreeableness, Conscientiousness, Extraversion, Neuroticism, Openness) as categorical data, and bring them together into a single 2D plot. The category for personality traits were determined by teams that scored *high* on any trait. Team personality was calculated by averaging the trait scores of both team members. High was determined by teams that scored at least one standard deviation (or 68th percentile) above the mean of the U.S. & Canada comparison sample. From the participant responses, 13 teams scored high in at least one trait, whereas the remaining 5 teams did not. Five teams scored high for Agreeableness, 11 teams for Conscientiousness, one team for Openness, one team for Extroversion, and no teams for Neuroticism. Due to these low sample sizes, the use of CA was not justified.

In the correlation analysis, each team personality trait was correlated to system levels (level 1, 2, 3, O) and system processes (decomposition, recomposition, same level). Eighteen teams were considered in the analysis (N = 18). Pearson correlation output from SPSS are summarized in Table 12. No significant results were found at the 0.05 significant level.

Table 12

Pearson Correlation Results

Trait		System 1	System 2	System 3	System O	Decompo-sition	Recompo-sition	Same Level
E	Pearson Correlation	-0.322	-0.135	0.229	0.014	-0.317	-0.294	0.307
	Sig. (2-tailed)	0.192	0.594	0.360	0.956	0.200	0.237	0.216
	N	18	18	18	18	18	18	18
A	Pearson Correlation	0.059	0.022	-0.067	0.109	0.263	0.268	-0.266
	Sig. (2-tailed)	0.816	0.932	0.791	0.666	0.292	0.283	0.286
	N	18	18	18	18	18	18	18
C	Pearson Correlation	-0.316	-0.407	0.390	0.046	-0.174	-0.201	0.188
	Sig. (2-tailed)	0.201	0.094	0.110	0.857	0.489	0.423	0.456
	N	18	18	18	18	18	18	18
N	Pearson Correlation	0.135	-0.178	0.099	-0.204	-0.061	-0.137	0.098
	Sig. (2-tailed)	0.592	0.480	0.696	0.417	0.809	0.587	0.699
	N	18	18	18	18	18	18	18
O	Pearson Correlation	-0.139	-0.059	0.078	0.095	-0.064	-0.076	0.070
	Sig. (2-tailed)	0.582	0.815	0.758	0.707	0.801	0.763	0.783
	N	18	18	18	18	18	18	18

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).
Trait: E = Extroversion, A = Agreeableness, C = Conscientiousness, N = Neuroticism, O = Openness.
N = 18 teams.

ANCOVA sought to measure personality traits and systems thinking while controlling for design experience. Professionals were assumed to have more design experience than engineering students. The covariate was grouped by professionals, seniors, and freshmen to rank their design experiences from highest (professionals) to lowest (freshmen). System levels and system processes were the dependent variable and personality traits were the independent variable. ANCOVA p-values for test of between

subject effects for N=18 teams are summarized in Table 13. The results show that no significant differences were found in personality traits with system levels and system processes. On the contrary, the covariate, design experiences, showed significant differences for all system levels and system processes.

Table 13

ANCOVA Results

Test of Between-Subjects Effects (p-Value)	Level 1	Level 2	Level 3	Level O	Decomp-osition	Recomp-osition	Same Level
Covariate (Design Exp.)	0.001**	0.012*	0.000**	0.001**	0.012*	0.016*	0.014*
Personality Trait	0.177	0.716	0.243	0.898	0.439	0.499	0.467

*$p \leq 0.05$
**$p \leq 0.01$
N = 18 teams

CHAPTER V

DISCUSSIONS, IMPLICATIONS, AND RECOMMENDATIONS

Systems thinking is considered to be both a cognitive ability (Behl & Ferreira, 2014; Chan, 2015; Crawley et al., 2016; Rouse, 2003; Ryen, 2008;) as well as a practical skill (Frank, Sadeh, & Ashkenasi, 2011; Simpson & Martins, 2011; Robinson-Bryant, 2018). It is a competency that is lacking in engineering education (Robinson-Bryant, 2018; Simpson & Martins, 2011; Wasson, 2012) and the engineering workforce (Armstrong & Wade, 2015; Davidz, 2006; Heidi & Martin, 2011). This competency is a favorable characteristic among practicing engineers, especially in design of complex engineering systems (Frank, 2000; Godfrey et al., 2014; Gonçalves & Britz, 2009).

In the design of complex systems, systems thinking adopts a hierarchical view that the complex system can be decomposed into solution elements, which consist of subsystems, parts, and components (Higgins, 2004; Rouse, 2003). Solution elements, which are usually well-known and well-designed (Rouse, 2003), are products of a decomposition process that can be recomposed to form the desired functions or the big picture goals of design (Behl & Ferreira, 2014; Chan, 2015; Godfrey et al., 2014; Robinson-Bryant, 2018). The ability to see the big picture, or the system as a whole rather than in parts, is an important element of systems thinking (Chan, 2015; Godfrey et al., 2014; Robinson-Bryant, 2018; Ryen, 2008).

Systems thinking is found to be both a result of education and work experience as well as the personality characteristics of the individual (Davidz, 2006; Frank, 2000). This is basically a question of nurture and nature. Nurture refer to systems thinking as a result of education and work experience, whereas nature refer to the personality characteristics

of the individuals. The literature suggest evidence for this dual view of systems thinking, however, more studies are needed to further understand the nurture and nature of a designer's ability to systems think.

Through the lens of engineering education, this study investigated systems thinking of experts and novices in engineering design to address the dual view. In view of systems thinking because of engineering education and work experience – the nurture argument, this study dedicated three research questions (1-3) to investigate differences in systems thinking of experts and novices. The assumption here is that experts have more design experience and they are therefore the benchmark for novices. In view of systems thinking because of individual personalities and characteristics – the nature argument, this study *explored* the relationship between systems thinking and personality traits through research question 4. Based on the results obtained from Chapter IV, the research questions and their hypotheses are discussed and compared to the scientific literature.

Systems Thinking as Big Picture vs Details

Research Question 1 purport to measure systems thinking between experts and novices through their top-down and bottom-up problem-solving strategy. Consistent with terms used in the literature, a top-down problem-solving strategy is problem decomposition and a bottom-up problem-solving strategy is problem recomposition. The researcher hypothesized (H1) that experts will problem decompose and recompose more than novices. Experts were professional engineers and novices were freshmen and senior engineering students. Problem decomposition and recomposition are processes of the

system levels (as defined in Table 4). Therefore, a discussion of expert-novice system levels precedes expert-novice problem decomposition and recomposition.

A closer look at the system levels in Table 6 show that professionals and seniors spend their time thinking twice as much in system level 1 than freshmen. System level 1 is thinking about the system as a whole (as defined in Table 3), where designers adopt a holistic or big picture view of the design problem. It is concerned with design functions, design goals, and desired outputs of the system that are at the top level of the system hierarchy (see Figure 1). On the contrary, freshmen spend nearly 1.5 times more time than professionals and seniors in system level 3. System level 3 is thinking about the details of the system, where designers analyze the parts and components of the system, which are at the bottom level of the system hierarchy. System level 2 is the relay between system level 1 and system level 3. It is the middle level in the system hierarchy and is concerned with subsystems or subproblems of the complex system. This is where designers consider partial behaviors of the system, major structures of the system, and user interactions with the system. Professionals and seniors were nearly 1.5 times higher than freshmen in system level 2. The differences between professionals and seniors to freshmen were statistically significant ($p > 0.01$). No significant difference was found between professionals and seniors. The effect size for system levels 1, 2, and 3 ranged from 0.3 – 0.4, which is much greater than the threshold of 0.14. Therefore, differences in expert-novice is considered to have a large effect for system levels 1, 2, and 3.

It can be concluded that there are no differences in systems thinking of professionals and seniors at the system levels. Specifically, professionals and seniors adopted a holistic or big picture view of the design problem. One explanation is that

seniors were expert-like in their ability to realize the bigger picture of their design such as economics, ergonomics, safety, and the impact on various stakeholders such as the customers. This was lacking among the freshmen. Instead, the freshmen adopted a microscopic or detailed view of the design problem; they were more concerned with analysis and details of the design problem than their counterparts. Moreover, professionals and seniors were able to identify more subsystems and subproblems of the complex design problem than freshmen. The ability to identifying subsystems and subproblems is aided by their ability to decompose complex systems into solution elements. This is discussed next.

Problem decomposition is a strategy to solve complex engineering design problems (Gralla et al., 2017; Higgins, 2004; Ho, 2001; Song, 2014). It breaks complex problems into smaller and manageable solution elements, which consist of subsystems and subproblems that can be further broken down into parts and components (Rouse, 2003). Problem recomposition is the reverse process of decomposition. In view of a complex system as a hierarchy, problem decomposition and recomposition are processes of going from one system level to another. The system processes are described in Table 4. If the process is going from a higher level to a lower level, e.g. from system level 1 to level 2 ($1 \rightarrow 2$), it is a top-down or problem decomposition process. If the process is going from a lower level to a higher level, e.g. from system level 2 to level 1 ($2 \rightarrow 1$), it is a bottom-up or problem recomposition process.

Based on the results in Table 7, a significant difference was found in problem decomposition and recomposition for professionals and freshmen, seniors and freshmen, however, no significant differences were found for professionals and seniors. In order to

reject the null hypothesis, professionals must be significantly different to *both* freshmen and seniors. Therefore, because the *p*-value is greater than the significance level for professionals and seniors, we failed to reject the null hypothesis - that experts and novices problem decompose and recompose the same. A failure to reject the null hypothesis in a significance test does not mean that the null hypothesis is true. It only means that the we were unable to provide enough evidence for the alternative hypothesis. We conclude that there was no difference in the problem decomposition and recomposition of professionals and seniors. This conflicts with results from a previous pilot study that found seniors and freshmen to be alike in problem decomposition and recomposition (Song, 2014). The results of this research show that seniors and professionals decomposed and recomposed significantly more than freshmen and the effect size for this difference was large. One explanation is that seniors have received some education in solving complex design problems through senior capstone, engineering ethics, multidisciplinary engineering, or similar courses. The freshmen preferred the alternative to problem decomposition and recomposition, which was to stay at the same level.

Same level is the alternative to a top-down (decomposition) or bottom-up (recomposition) movement in the system hierarchy. It is a horizontal traverse in the system hierarchy. Cognitively, this means that when the designers are at a system level, they stay at that level and do not jump vertically to system levels above or below. Freshmen tend to do this more than professionals and seniors, about 10% more. The difference was significant, and the effect was large. In order to explain why this is the

case, it requires a deeper look at the probability distributions of system processes for the three cohorts. This is explained using Markov analysis and the results shown in Table 8.

From Table 8, there is almost an 80% chance for freshmen to stay in the details level, which is level 3 to level 3 (3→3). In fact, problem decomposition and recomposition show that freshmen are more likely to move towards the details from any other system level. The effect size ranged from 0.17 to 0.36, which is considered to have a medium to large effect. This shows a strong desire for freshmen to analyze details of the system. Based on the literature, there are multiple possible explanations for this: 1) This is a reflection of their early engineering education experience – they are detail oriented and focus on analysis such as application of equations to well-structured problems (Gray, Costanzo, & Plesha, 2005; Song, 2014), 2) They have low tolerance for ambiguity – once they talk about the details, then all the details must be flushed out before they move on. This confirms earlier studies that found freshmen to be frustrated when details of the problem are unknown (Song, 2014) and not accepting ambiguity in the design of ill-structured problems (Dringenberg & Purzer, 2018), 3) A lack of confidence to work with bigger, more complex, and ill-structured problems that are higher up in the system hierarchy. Instead, they are fixated in the details level. Fixation is a designer's tendency to adhere to existing features from the examples they encounter in their immediate surroundings or day-to-day activities (Viswanathan, Esposito, & Linsey, 2012). This is common in engineering design (Corley & Hartsuiker, 2011), but freshmen in particular, tend to fixate on features of examples that they have encountered (Viswanathan et al., 2012). The examples that freshmen encounter in engineering

classrooms are mostly well-structured and oriented towards detailed analysis (Jonassen, Strobel, & Lee, 2006), which help explain their fixation on details.

On the other hand, seniors demonstrate the ability to systems think like professionals, the experts, in viewing the system as a whole. Through a holistic view, they realize the big picture functions, objectives, and goals of the design, which are complex. The complexity was partitioned into manageable subsystems, subproblems, and all the way down to the details via a decomposition strategy. The details are then synthesized into subsystems, sub-solutions, and all the way back up to the overall functions, objectives, and goals via a recomposition strategy. There are several reasons why seniors were expert-like in this regard, more importantly, a transformation from detail oriented as freshmen to more big-picture oriented as seniors. 1) Capstone Design. The senior students take a senior Capstone Design course, which is required by the college of engineering. The educational experiences of Capstone Design, and the transfer of this experience into complex engineering design may be accountable for seniors' expert-like systems thinking. 2) Level of difficulty in the design task. Level of difficulty of the design task can be defined in terms of complexity such as breadth of knowledge required and intricacy of procedures, and structuredness such as interdisciplinarity and heterogeneity of interpretations (Jonassen & Hung, 2008). A design task that is difficult for freshmen may not be as difficult for seniors and professionals if they encountered similar design problems in their engineering courses or work experiences. Therefore, the level of difficulty in the task may have contributed to the finding. Future studies should explore systems thinking with different design tasks that vary in level of difficulty. 3) A change in age and maturity. Years of experience was the criterion for the selection of

experts. Then, the time it takes for a freshman to become a senior should not be discounted. The progression from freshmen to sophomore, then junior, and eventually senior, is at least four years. Studies have shown that a young adult, who is immersed in a socially rich environment such as a university, matures over time (Rodriguez, 2012; Sharma, 2012). Senior engineering students' maturity was reflected in the design of complex engineering problems through a breadth of considerations about multiple stakeholders (customers, government officials, etc.) and big picture concerns (e.g. economics, aesthetics, safety etc.) that affect the system, as opposed to freshmen's tendency to be centered around details.

Although seniors were like experts in systems thinking as a holistic view, they were found to be different in the problem-solution focus of systems thinking. This is discussed next.

Systems Thinking in Problem Space vs Solution Space

Systems thinking as system levels and system processes can either occur in the problem space or solution space. Designers are either trying to understand the problem – problem space, or they are trying to find solutions to the problem – solution space. The researcher hypothesized that professionals will have more systems level 1 (H2) and problem decomposition in the problem space (H3) than students.

Based on the results from Table 9, we reject the null hypothesis for H2, that professional engineers and engineering students are the same for system level 1 in the problem space, and accept the alternative hypothesis that professionals have more system level 1 in the problem space. Based on the results from Table 10, we reject the null

hypothesis for H3, that professionals and engineering students are the same in problem decomposition in the problem space, and accept the alternative hypothesis that professional engineers have more problem decomposition in the problem space than engineering students.

Results in Tables 9 and 10 show that systems thinking of experts are more problem focused than novices in system level 1, level 3, and problem decomposition. Significant differences were found at all system levels and processes except for system level 2. The effect size for the differences in experts' and novices' problem focus versus solution focus ranged from 0.11 to 0.31, which is considered to have a medium to large effect. This finding is not unique, as other studies in expert-novice design have come to similar conclusions (Atman et al., 2007; Becker et al., 2019; Ho, 2001; Song, 2014). However, in the context of systems thinking, the results show that seniors are like experts in some ways and like freshmen in other ways. This finding opens opportunities for future researchers to investigate the problem-solution focus of systems thinking. One way is to explore the solution-space by comparing the artefacts of their design such as sketches and documentation. Doing so may unveil further differences in expert versus novice systems thinking that were not found in this study.

The results from this study showed that professionals think about the big picture functions, objectives, and goals of the design in the problem space more than seniors and freshmen. This is shown in Table 9 where the PS-Index for level 1 was 0.50 for professionals, 0.33 for seniors, and 0.35 for freshmen. Professionals' tendency to understand the big picture of the design problem could be due to expert training or experiences that encourage a problem focus to obtain optimal solutions in complex

designs. Comparatively, seniors and freshmen had lower PS-Level 1, which means that they were inclined to consider the big picture of the design in the solution space over the problem space. This behavior resonates with previous expert-novice studies that found students to spend significantly less time than expert practitioners in problem scoping and information gathering, which are essential for understanding the design problem before the search for design solutions (Atman et al., 2007; Ho, 2001). Additionally, this finding supports existing literature that found experts to gather information that are more diverse and cover more categories compared to students (Atman et al., 2007).

No significant differences in problem-solution focus was found at the subsystem level for professionals, seniors, and freshmen. However, at the details level, professionals and seniors were more problem focused than freshmen. Professionals and seniors were about 1.5 times more likely to focus on the problem than freshmen. This difference was significant with a large effect. One explanation is that professionals and seniors analyze details of the system to further learn and understand the problem, whereas freshmen analyze details of the system to find solutions to the problem – they want answers. This was made explicit by Mina & Gerdes (2006) that 21st century freshmen engineering students do not seek to find understanding through learning, but only answers. According to the author, a probable cause for this behavior and attitude is the availability of technology and access to information, which they have become accustomed to from earlier educational experiences and gaming activities. Furthermore, Table 10 shows that freshmen and seniors were more solution focused when decomposing and staying at the same level in the system hierarchy. A student’s tendency towards the solution space over the problem space is significantly higher than experts with a large effect. This evidence

illustrates a student's desire to pursue solutions to the problem over understanding of the problem. To some extent, it confirms that a freshmen's tendency towards the solution persist throughout their academic career including the senior year (Mina & Gerdes, 2006). On the other hand, freshmen differed from seniors because freshmen were expert-like in their recomposition process in the problem space.

The differences between experts' and novices' problem-solution focus can be explained by the problems they encounter in their environments. The well-structured problems that engineering students solve do not fully reflect the problems that professional engineers solve at the workplace (Jonassen et al., 2006). Professional engineers work with well-structured and ill-structured problems that often include both engineering and non-engineering considerations in the problem space. However, engineering classrooms provide little opportunity for ill-structured problems and non-engineering considerations in problem-solving (Daniels, Carbone, Hauer, & Moore, 2007; Jonassen et al., 2006). Consequently, students have limited access to non-engineering considerations in the problem space that professionals bring into design.

Systems Thinking and Team Collaboration

Teams are an essential feature of engineering, especially when solving dynamic and complex problems (Gyory et al., 2019; Hsu, 2017; Lerdahl, 2001; Oladirana et al., 2011). In practice, engineering design teams are encouraged to develop and construct design solutions through collaboration of individual expert knowledge and experience (Flanagan et al., 2007), creativity (Lerdahl, 2001), and work values (Hsu, 2017). In this study, experts and novices worked in teams of two to solve a complex design problem.

Interactions between the utterances of the two members were measured. In particular, the researcher was interested in interactions of team members when they problem decomposed. The researcher hypothesized that (H4) professional engineers will use problem decomposition more as team interactions increase compared to engineering students.

Readers should be aware that using turn taking as the measure of interaction is a weak model as it only accounts for the interactions based on system processes (problem decomposition, recomposition, same level) and not to the full extent of the content, which is the basis of team collaboration. Evidence of interaction through turn taking could suggest that there is team collaboration. Based on the results in Table 11, we reject the null hypothesis that professionals and students use problem decomposition the same when they interact, and we accept the alternative hypothesis. However, the evidence does not support H4. In fact, it is the other way around; engineering students used problem decomposition more as team interactions increase compared to professional engineers. This result was unexpected. Both seniors and freshmen were significantly higher than professionals in decomposition-interactions. No significant difference was found between seniors and freshmen in decomposition-interactions. One explanation for professional engineers' lower team interactions may be due to the differences in expert and novice reflective process in engineering design. Reflection is an internal process of engaging and interacting with one's own thoughts and actions (Nguyen, Fernandez, Karsenti, & Charlin, 2014). Expert engineers tend to reflect continuously throughout the design process, whereas novices only reflect upon a non-working solution or a mistake (Harlim & Belski, 2013). The reflective process shed light on the low team interactions for

problem decomposition and recomposition. The teams spent about 22% of their interactions on problem decomposition and recomposition. A majority of their interaction was engaged with design activities other than systems thinking, most of which were interactions with themselves. The tendency of designers to build on their own ideas or interact with themselves is common in design team behavior (Gero, Kan, & Jiang, 2014) and may explain the low team interactions in this study. Furthermore, readers should acknowledge that team collaboration before and after the design activity, which is common practice in real world engineering, is unknown because this study was cross sectional and not longitudinal.

While many factors influence the behavior of teams, individual personalities of team members in particular have been shown to affect the performance and effectiveness of design teams (DuPont & Hoyle, 2015; O'Neill & Allen, 2011; Shen et al., 2013; C. Toh et al., 2013; Trenshaw & Vogel, 2014; Varvel et al., 2004). This alludes to the role of personalities and characteristics of individuals on systems thinking. The systems literature claims that there is a relationship between systems thinking and the individual personalities. This is discussed next.

Systems Thinking and Personality Traits

Evidence in the systems thinking literature claims that there is a relationship between systems thinking and personalities of systems thinkers (Armstrong & Wade, 2015; Behl & Ferreira, 2014; Davidz, 2006; Frank, 2000, 2006; Heidi & Martin, 2011). The researcher explored this relationship via correspondence analysis (CA), correlation, and analysis of covariance (ANCOVA). Eighteen teams (N=18 teams, n=36 persons)

completed The Big Five Inventory personality survey (Soto & John, 2009) and formed the data for analysis. Due to the limitations on sample size, readers should interpret the results and discussions of this section with circumspect. While the results from this exploratory analysis are not generalizable, it does provide evidence to support the existing literature and inform future research.

As expected, the personality profiles of engineers (shown in Figure 10) in this study align with results from other studies. Consistent with Knauerhase & Hahn (2008), engineers scored lower in extraversion, which means they tend to be introverts. Engineers scored low in neuroticism, which means they tend to be emotionally stable, and scored high in conscientiousness, which means they tend to be organized, responsible, and have a strong will to achieve. This finding is consistent with results from earlier studies (Van Der Molen et al., 2007; Williams, 2009; Williamson et al., 2013).

Contrary to the belief that engineers are tough minded and low in agreeableness (Van Der Molen et al., 2007; Williams, 2009), the results from our sample of 36 engineers show that they are more agreeable than an average engineer in the U.S. and Canada. There are three possible explanations for this: 1) The participants that took the survey happen to be highly agreeable due to random chance or luck. 2) By definition of agreeableness (Digman, 1990), agreeable participants are more likely to fill out voluntary surveys because they are courteous, flexible, trusting, good natured, cooperative, conforming, forgiving, soft-hearted, and tolerant. 3) A cultural and religious differences between the States in the U.S. Thirty-two out of 36 participants were from the State of Utah, the remaining 4 were from the state of California. Currently, Utah is known to be a state that is home to the Latter Day Saints (LDS) religion. A recent study showed that the

personality traits of the members of the LDS church scored high in Agreeableness (Allen, Hafoka, & Fischer, 2019). Agreeableness, which is being kind and understanding, is a valued attribute among LDS people. Despite the assumption that personality traits are independent of the environment, the religious teachings and believes may have played a role in shaping an average Utahn engineer to be more agreeable.

As shown in the CA, agreeableness and other personality traits were associated with systems thinking (shown in Figure 11). Consistent with the literature, high agreeableness, which infer the ability to work in teams, was considered an essential characteristic for systems thinkers (Armstrong & Wade, 2015; Behl & Ferreira, 2014; Frank, 2000). The pilot data supports this evidence and suggests that engineers that are highly agreeable are associated with adopting a holistic view and problem decomposition and recomposition strategies. High conscientiousness, which have characteristics of being organized, responsible, and high achieving, was found to be a common trait among systems engineers (Davidz, 2006). This is reflected in the pilot data and it suggests that highly conscientious engineers work hard to cover a breath of possibilities, as well as depth during their systems thinking process.

Results from correlation and ANCOVA found no statistical significance for systems thinking and personality traits. One reason is that there was insufficient data in the analysis. Another reason is that the acclaimed relationship in the literature does not exist.

To address the dual view of systems thinking due to nature and nurture, the results of this study help understand the nurture side. Specifically, it identified the differences between expert and novice systems thinking. However, the exploratory results on the

relationship between systems thinking and personality show no clear evidence and require more data to substantiate the findings before further conclusions can be made.

Implications

This study compared systems thinking of experts and novices when designing complex engineering systems. The reader is encouraged to reflect on how the results and conclusions of this study may be valuable to their unique research and educational endeavors. The reader should also acknowledge the context in which systems thinking was investigated and the limitations of the study.

The limitations emerge from the participants. First, a majority of the participants were white male. This does very little to shed knowledge on minorities and less represented groups in engineering. Second, the participants were mainly from Utah, and only two teams were from California. This only represents two States out of the entire U.S. Third, research question #4 *explored* systems thinking as it relates to personality traits because of a small sample size and assumptions about participant age. While the results from this study can help inform engineering education, readers are cautioned to interpret the results within context and extrapolate the findings as appropriate.

From the results of this study, it can be inferred that experts and novices are different in systems thinking. While the difference between experts and freshmen were clear, the difference between experts and seniors were not as obvious. Seniors demonstrated expert-like systems thinking in some ways and freshmen-like in other ways. This implies that engineering education should be commended for developing systems thinking capabilities in their students through their engineering programs.

However, experts distinguished themselves from novices through significantly higher big picture thinking and problem focus. This gap can be addressed through engineering pedagogy with the help of engineering educators. In doing so, educators should acknowledge that there are constraints and challenges to changing curriculum, such as accreditation boards (e.g. ABET) and instructor preferences. Therefore, educators are encouraged to adapt the findings and implications of this study to their unique environments.

Engineering educators should incorporate and encourage big-picture thinking in their classrooms. This is not to say that instructors should assign complex design problems, like the one in this study, to enable students to think in the big-picture. Instead, expose and introduce engineering students to graphical representation, or a systems architecture, of everyday systems and problems that they encounter in the classroom. It provides a platform for systems thinking and is shown to improve student learning process through self-reflection (Godfrey et al., 2014). One way to incorporate systems architecture into the classroom is to have a hierarchical graphic representation of the course materials to supplement the course descriptions in the syllabus. In this view, the system is the course and the architecture is the graphical representation of the course materials that are organized in hierarchies. Doing so fosters visual learning, which is considered an important learning strategy for engineering education (Mcgrath & Brown, 2005), and may help students in three ways: 1) They can see the big picture of their work especially when they are engaged in the detailed analysis. 2) They can use the graphic as a reference to organize their thoughts and see interconnections between topics. This may

help with their conceptual understanding of the topic. 3) They may establish a habit to see the big picture through practice and experience.

In addition to big-picture thinking, engineering educators, especially in the senior capstone classes, should place a stronger emphasis to understand the complex design problem and customer requirements. This study has shown that experts systems think in the problem space, whereas seniors and freshmen alike prefer the solution space. To bridge this gap, engineering educators are encouraged to accommodate good student and stakeholder relationships to create a safe, realistic, and controlled environment for learning (Behdinan, Pop-Iliev, & Foster, 2015; Bielefeldt, 2005). Stakeholders include customers, course instructors and assistants, administrative representatives, government officials, and subject matter experts, among others. In this environment, students are *not discouraged* to communicate and interact with their stakeholders to obtain a breadth of design functions, objectives, and goals. On one hand, this may help guide students into the problem space during the systems thinking process. On the other hand, the designed products are more thoroughly thought out to meet customer requirements and industry expectations.

As one of the main employers of engineering graduates, industry, is encouraged to go beyond partnering with universities for senior design projects and play a more active role in engineering curriculum design. Companies that seek systems thinking capabilities of their workforce should have a direct interest in the expectations and outcomes of engineering design education. One way to contribute is to get involved with the Accreditation Board for Engineering and Technology (ABET). Use evidence from this study and similar studies to advocate the competencies and systems thinking skills that

industry would like to see in their engineers into engineering curriculums. For example, require engineering programs to incorporate internships into their curriculum. Internships serve as a bridge between experts in industry and novices in academia. More importantly, it opens opportunities for students to work in real world complex engineering problems.

Complex, ill-structured, or open-ended problems, which are typical in real-world engineering, are less popular in engineering education for the convenience of specification and assessment (Daniels et al., 2007). Instead, well-structured problems are used as learning examples. The consequence of this can be implied from the results of this study. Contrary to expert behavior, students become detail oriented when solving complex problems and forego the importance of the big picture. This is not to say that being detail oriented is negative in anyway. Instead, big-picture thinking should be encouraged, especially earlier in the engineering program (freshmen and sophomore courses), which are typically are very structured. Adding content to the already overloaded courses is not the solution. Instead, engineering educators are encouraged to be creative in fostering big-picture thinking into their classes. As mentioned earlier, one way is to implement an architecture of the course contents into syllabus. Other ways include assessment of conceptual understanding, for example, ask students, ‘is this a dynamic or static problem?’, before asking, ‘what is the force at this point?’, and implement Problem Based Learning to expose students to open-ended engineering problems.

This study found that systems thinking is primarily an individual activity rather than a team activity. Though, readers should be aware that using turn taking as the measure of interaction is a weak model as it only accounts for the interactions based on

system processes (problem decomposition, recomposition, same level) and not to the full extent of the content. Therefore, evidence of team interaction could suggest that there is team collaboration. If so, the findings here play to the strength of individual learning. Engineering educators do not have to assume that a team is required for expert-like, top-down problem-solving strategy, or novice-like, bottom-up problem-solving strategy, as found in earlier studies (Ho, 2001; Song, 2014). Instead, both problem-solving strategies can be performed individually.

Finally, exploratory results from the correspondence analysis of personality traits and systems thinking support prior literature that claim systems thinkers to be highly agreeable and conscientious (Armstrong & Wade, 2015; Behl & Ferreira, 2014; Davidz, 2006; Frank, 2000). However, Openness, Extroversion, and Neuroticism remain unknown due to lack of data. Additionally, no statistical significance was found in the correlation and ANCOVA. The findings were based on a small sample size, therefore, the relationship between personality traits and systems thinking remain an opportunity for future research.

Recommendations for Future Research

Based on the findings of this study, there are several recommendations for future research:

On Methodology. The researcher demonstrated that the methodology used in this study is a viable method to measure and assess systems thinking. However, this does mean that future researchers should be trained and be familiar with the nuance of Function-Behavior-Structure (FBS) Ontology. FBS is a quantitative approach for

research in design protocols. The method is detailed in a book recently published by Dr. John Gero and colleague titled ‘Quantitative Methods for Studying Design Protocols’ (Kan & Gero, 2017). It is recommended that researchers who are interested in FBS and systems thinking use this book in conjunction with the method described in this study. Alternatively, other frameworks that purport to quantitatively and qualitatively measure systems thinking could be explored, designed, and implemented. This provides the systems and engineering education research community more options and flexibility for future research.

On Participants. Future studies should aim to recruit participants that are: geographically diverse to cover other parts of the U.S. beyond Utah and California, ethnically diverse to represent minorities groups such as African Americans and Hispanics, and gender diverse to include females and LGBTQ that are underrepresented in engineering. Furthermore, the researcher assumed senior and freshmen students to be novices based on the literature review. However, the results indicate that seniors lie in between freshmen and expert systems thinking. Therefore, it is recommended that future studies distinguish freshmen from seniors like this study and avoid combining the two groups without justification. Moreover, this study recruited participants from mechanical, civil and environmental, and biological engineering. It would be interesting to investigate systems thinking of each discipline so that departments within the college of engineering could lend to benefit from each other’s strengths.

On Experimental Design. This study was cross-sectional given the single one-hour design challenge, which does not fully exemplify real-world complex engineering that may take up to weeks, months, or even years. Therefore, it is recommended that

future studies utilize longitudinal research methods in classes such as senior capstone to measure temporal effects on systems thinking. Alternatively, more complex design problems that are expected to take longer than an hour to solve could also be used. Additionally, this study was quantitative. Future research questions could address systems thinking through a qualitative or mixed methods approach. One justification is that while systems thinking can be measured quantitatively, the personalities of engineers are difficult to quantify, therefore, a qualitative or mixed methods approach may be more appropriate.

On Personality and Systems Thinking. This study explored the relationship between the Big Five personality traits and systems thinking with limited sample size and assumptions about the participants. Future studies that seek to better understand this relationship should: 1) Include a larger sample to capture all five personality traits in their analysis. 2) Use alternative Big Five personality assessment instruments such as the Revised NEO Personality Inventory (Costa & McCrae, 2008) and Goldberg's Markers for the Big Five Factor (Goldberg, 1992), which have more questions compared to the Big Five Inventory (Soto & John, 2009). 3) In the experimental design, the researcher should assess the personalities of the participants first, then place them in teams through a selective process to solicit dominant traits and relating it to systems thinking. 4) Systems and educational researchers should seek to collaborate with researchers in business and psychology that share similar interests in systems thinking.

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APPENDICES

Appendix A: Big Five Inventory (BFI) Questionnaire

Here are a number of characteristics that may or may not apply to you. For example, do you agree that you are someone who *likes to spend time with others*? Please write a number next to each statement to indicate the extent to which you agree or disagree with that statement.

The Big Five Inventory

Disagree strongly	Disagree a little	Neither agree nor disagree	Agree a little	Agree strongly
1	**2**	**3**	**4**	**5**

I see myself as someone who...

__1. is talkative
__2. tends to find fault with others
__3. does a thorough job
__4. is depressed, blue
__5. is original, comes up with new ideas
__6. is reserved
__7. is helpful and unselfish with others
__8. can be somewhat careless
__9. is relaxed, handles stress well
__10. is curious about many different things
__11. is full of energy
__12. starts quarrels with others
__13. is a reliable worker
__14. can be tense
__15. is ingenious, a deep thinker
__16. generates a lot of enthusiasm
__17. has a forgiving nature
__18. tends to be disorganized
__19. worries a lot
__20. has an active imagination
__21. tends to be quiet
__22. is generally trusting
__23. tends to be lazy
__24. is emotionally stable, not easily upset
__25. is inventive
__26. has an assertive personality
__27. can be cold and aloof
__28. perseveres until the task is finished
__29. can be moody
__30. values artistic, aesthetic experiences
__31. is sometimes shy, inhibited
__32. is considerate and kind to almost everyone
__33. does things efficiently
__34. remains calm in tense situations
__35. prefers work that is routine
__36. is outgoing, sociable
__37. is sometimes rude to others
__38. makes plans and follows through with them
__39. gets nervous easily
__40. likes to reflect, play with ideas
__41. has few artistic interests
__42. likes to cooperate with others
__43. is easily distracted
__44. is sophisticated in art, music, or literature

Please check: Did you write a number in front of each statement?

Appendix B: BFI Scoring Instructions

To score the BFI, you'll first need to **reverse-score** all negatively-keyed items:

Extraversion: 6, 21, 31

Agreeableness: 2, 12, 27, 37

Conscientiousness: 8, 18, 23, 43

Neuroticism: 9, 24, 34

Openness: 35, 41

Example (Extraversion): Survey questions 6, 21, and 31 correspond to answering questions about extraversion. These three items need to be reverse-scored following the instructions below.

To reverse score (recode) these items, you should subtract your score for all reverse-scored items from 6. For example, if you gave yourself a 5, compute 6 minus 5 and your recoded score is 1. That is, a score of 1 becomes 5, 2 becomes 4, 3 remains 3, 4 becomes 2, and 5 becomes 1.

Next, you will create scale scores by ***averaging*** the following items for each Big Five domain (where R indicates using the reverse-scored item).

Extraversion: 1, 6R 11, 16, 21R, 26, 31R, 36

Agreeableness: 2R, 7, 12R, 17, 22, 27R, 32, 37R, 42

Conscientiousness: 3, 8R, 13, 18R, 23R, 28, 33, 38, 43R

Neuroticism: 4, 9R, 14, 19, 24R, 29, 34R, 39

Openness: 5, 10, 15, 20, 25, 30, 35R, 40, 41R, 44

Example (Extraversion): Items 1, 6, 11, 21, 26, 31, and 36 are all items that answer questions about extraversion. 6R, 21R, and 31R indicates items that need to be reverse-scored. The final score is the average of all items that correspond to the

Appendix C: BFI Comparison Sample

Comparison Sample: Means and Standard Deviations for Big Five Inventory (John & Srivastava, 1999) by Age

		Extraversion		Agreeableness		Conscientiousness		Neuroticism		Openness	
AGE	*N*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
21	6076	3.25	.90	3.64	.72	3.45	.73	3.32	.82	3.92	.66
22	5014	3.26	.89	3.64	.72	3.50	.72	3.30	.82	3.94	.65
23	4828	3.30	.89	3.64	.70	3.52	.70	3.28	.82	3.94	.66
24	4494	3.28	.89	3.67	.70	3.55	.71	3.29	.82	3.95	.65
25	4499	3.31	.91	3.66	.71	3.58	.71	3.27	.83	3.96	.66
26	3683	3.31	.91	3.66	.70	3.57	.71	3.28	.83	3.95	.66
27	3529	3.28	.91	3.68	.69	3.60	.71	3.26	.82	3.95	.66
28	3497	3.29	.92	3.67	.70	3.61	.71	3.23	.83	3.94	.66
29	3213	3.29	.91	3.67	.70	3.61	.70	3.25	.83	3.93	.67
30	3007	3.28	.90	3.67	.69	3.63	.72	3.22	.84	3.94	.67
31	2307	3.31	.90	3.68	.71	3.63	.72	3.24	.83	3.92	.67
32	2111	3.27	.89	3.72	.68	3.63	.72	3.21	.84	3.93	.67
33	1907	3.26	.92	3.75	.68	3.65	.72	3.20	.83	3.91	.67
34	1735	3.29	.93	3.73	.69	3.66	.73	3.19	.84	3.92	.67
35	1760	3.29	.91	3.75	.68	3.68	.73	3.19	.85	3.90	.68
36	1509	3.24	.91	3.78	.68	3.65	.74	3.19	.86	3.87	.70
37	1541	3.26	.92	3.82	.68	3.72	.72	3.15	.84	3.88	.69
38	1406	3.23	.90	3.84	.66	3.74	.71	3.13	.85	3.87	.69
39	1269	3.23	.91	3.83	.67	3.75	.71	3.17	.84	3.88	.69
40	1393	3.30	.89	3.81	.67	3.74	.72	3.14	.84	3.88	.69
41	1115	3.25	.91	3.87	.66	3.76	.71	3.15	.87	3.86	.65
42	1244	3.25	.90	3.89	.65	3.76	.74	3.11	.86	3.90	.69
43	1064	3.22	.93	3.90	.66	3.75	.70	3.14	.88	3.88	.72
44	1051	3.26	.88	3.86	.66	3.79	.70	3.11	.87	3.93	.65
45	1135	3.22	.89	3.88	.67	3.77	.69	3.10	.87	3.90	.70
46	900	3.23	.91	3.93	.68	3.81	.73	3.05	.87	3.85	.75
47	856	3.25	.89	3.90	.67	3.84	.68	3.06	.90	3.92	.75
48	809	3.24	.91	3.90	.62	3.80	.69	3.09	.87	3.88	.69
49	735	3.21	.89	3.91	.63	3.83	.72	3.05	.90	3.89	.72
50	791	3.26	.90	3.97	.66	3.85	.71	2.98	.89	3.90	.70
51	600	3.29	.94	3.96	.65	3.88	.67	3.02	.92	3.91	.67
52	563	3.30	.87	3.91	.67	3.85	.71	3.05	.92	3.90	.72
53	456	3.25	.92	3.99	.64	3.82	.72	3.04	.90	3.91	.66
54	328	3.17	.91	4.01	.67	3.84	.69	3.03	.93	3.86	.75
55	346	3.25	.85	3.91	.65	3.87	.66	2.93	.83	3.89	.71
56	317	3.26	.85	3.93	.66	3.88	.71	2.96	.83	3.86	.71
57	246	3.12	.91	3.96	.68	3.84	.69	2.94	.95	3.85	.73
58	210	3.18	.89	4.02	.66	3.93	.73	2.98	.85	3.79	.73
59	161	3.13	.89	3.90	.66	3.88	.74	3.06	.96	3.80	.70
60	162	3.10	.85	3.99	.68	3.86	.71	2.92	.99	3.80	.73

These descriptive statistics appeared in Srivastava, S., John, O. P., Gosling, S. D., & Potter, J. (2003). Development of personality in early and middle adulthood: Set like plaster or persistent change? *Journal of Personality and Social Psychology, 84*, 1041-1053. They were converted to POMP (percentage of maximum possible) metric and graphed by gender and age for each Big Five dimension.

Appendix D: Example Data - Systems Processes for Professional Engineers

Systems Processes for Professional Engineers

	Systems Processes											
Session No.	1→1	1→2	1→3	2→1	2→2	2→3	3→1	3→2	3→3	Decomposition	Recomposition	Same Level
1	0.07	0.06	0.02	0.05	0.32	0.14	0.02	0.13	0.20	0.21	0.20	0.59
2	0.05	0.06	0.02	0.06	0.38	0.14	0.03	0.13	0.13	0.22	0.22	0.56
3	0.10	0.07	0.01	0.06	0.25	0.12	0.02	0.11	0.25	0.20	0.19	0.60
4	0.03	0.03	0.01	0.03	0.29	0.14	0.02	0.14	0.31	0.19	0.19	0.62
5	0.03	0.04	0.01	0.03	0.24	0.16	0.02	0.15	0.31	0.21	0.20	0.58
6	0.05	0.05	0.04	0.05	0.25	0.12	0.04	0.12	0.31	0.20	0.20	0.61
7	0.02	0.04	0.01	0.02	0.28	0.15	0.02	0.13	0.33	0.19	0.18	0.64
8	0.04	0.03	0.02	0.02	0.21	0.13	0.02	0.13	0.41	0.17	0.17	0.66
9	0.10	0.05	0.04	0.05	0.24	0.09	0.05	0.09	0.29	0.19	0.18	0.63
10	0.04	0.03	0.01	0.02	0.24	0.12	0.01	0.11	0.42	0.15	0.15	0.70
11	0.06	0.03	0.02	0.02	0.26	0.11	0.03	0.10	0.35	0.17	0.16	0.68
12	0.09	0.06	0.03	0.04	0.19	0.10	0.05	0.08	0.36	0.19	0.17	0.64
13	0.06	0.03	0.03	0.02	0.12	0.08	0.04	0.08	0.54	0.14	0.14	0.72
14	0.08	0.04	0.04	0.04	0.16	0.07	0.04	0.07	0.45	0.15	0.15	0.70
15	0.04	0.01	0.03	0.01	0.11	0.06	0.03	0.06	0.66	0.10	0.10	0.80
16	0.16	0.05	0.03	0.05	0.20	0.06	0.03	0.07	0.35	0.14	0.15	0.71
17	0.05	0.04	0.02	0.03	0.15	0.08	0.03	0.08	0.54	0.14	0.13	0.74
18	0.09	0.03	0.03	0.02	0.21	0.06	0.04	0.05	0.47	0.12	0.11	0.76
M	0.06	0.04	0.02	0.04	0.23	0.11	0.03	0.10	0.37	0.17	0.17	0.66
sd	0.03	0.02	0.01	0.02	0.07	0.03	0.01	0.03	0.13	0.03	0.03	0.07

M = Mean, *sd* = standard deviation. Decomposition, Recomposition, and Same Level were calculated by taking the sum of the respective systems processes where:

Decomposition = systems processes 1→2, 1 → 3, 2 →3. Recomposition = 2 →1, 3 →1, 3 →2. Same Level = 1 →1, 2 → 2, 3 →3.

CIRRICULUM VITAE

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Education

Ph.D., Engineering Education — Aug 2020
Utah State University, Logan, Utah

M.S., Mechanical Engineering — Dec 2019
Utah State University

B.S., Mechanical Engineering — May 2016
Utah State University

- Minor, Mathematics

Engineering Education

- Proposal Writing
- Research Writing (Conference Papers, Presentations, and Publications)
- Literature Reviews
- Qualitative and Quantitative Research Methods
- Experience with IRB and Trained in Ethical Research with Human Subjects
- Curriculum Development, Assessment, and Evaluation
- Online Education (Synchronous and Asynchronous)
- Public Speaking (to technical and non-technical audiences)

Teaching Experience

Instructor, ENGR 2270 – Computer Engineering Drafting (Software: AutoCAD) USU, College of Engineering — 2018-2019

- Recognized as Graduate Student Teacher of the Year by the College of Engineering at Utah State University — 2019-2020
- Curriculum Design and Development | Assessment | Evaluation

- Teaching/Learning Pedagogies including:
    - Project based learning – students were engaged with the course through a project where they had to sketch, design, edit, and 3D print. The goal was to transform an abstract idea into something tangible and usable at the end. In the process of doing so, students had to ask questions, iterate during the design process with feedback from the instructor and TAs, and finally 3D print their design.
    - Hands on learning – students develop competence in engineering drafting by using the software to complete their weekly assignments. The lectures introduce them to new concepts in engineering drafting and relate the concepts to tools and applications in the software through demonstrations. Students practice using the software by applying the appropriate drafting and modeling tools for their weekly assignments.
    - Multi-disciplinary learning – students came from multiple engineering disciplines, therefore, homework assignments were based on problems in civil, mechanical, and biological engineering. A context was provided for the problems, which introduced students to different but related disciplines in engineering and helped them understand the problems that they are solving.
    - One-on-One mentoring – during lab and office hours, myself and the TAs provided individual help to students who struggled to understand the course material or to use the software in their assignments. Explaining concepts in a way that align with their individual learning styles clarified their misconceptions and fostered understanding.
    - Certification – Throughout the semester, students complete an introduction to AutoCAD online module as part of the course. The online module was a supplement to the course and consist of videos, demonstrations, and examples. Upon completion and passing the comprehensive test, students obtain an Introduction to AutoCAD certificate.
    - Student Feedback – students liked the course overall. They especially liked it when I explained the context clearly, concisely, and related to industry practice. They also appreciated my availability and the individual help they received.

Research Experience

- Quantifying Differences Between Professional Expert Engineers and Engineering Students Designing: Empirical Foundations for Improved Engineering Education (NSF Grant Nos. 1463873 and 1463809)
- Engineering Systems and Design: 'Compare What Systems Theory Tells and What People Do' – Work in Progress
- Dissertation Research: Systems Thinking in Engineering Design: Differences in Expert Vs. Novice and Relationship to Personality Traits
- Function-Behavior-Structure Ontology of Design (translating customer requirements into design functions, behaviors, and physical structures)
- National Science Foundation Engineering Design and Systems Engineering Workshop
  Purdue University, West Lafayette, Indiana Oct 2019

Conference Papers and Presentations

Gero, J. S., Becker, K., **Luo, Y.** Almeida, L., Abdellahi, S., & Kan, W. T. J. Empirical Foundations for Improved Engineering Education: Differences Between Engineering Students and Professional Expert Engineers while Designing. *Proceedings of the American Society for Engineering Education 2019 Annual Conference, Tampa, FL.*

Becker, K., Gero, J. S., & Pourmohamadi, M., & Abdellahi, S., & de Souza Almeida, L. M., & **Luo, Y.** (2018, June), *Quantifying Differences Between Professional Expert Engineers and Engineering Students Designing: Empirical Foundations for Improved Engineering Education* Paper presented at 2018 ASEE Annual Conference & Exposition , Salt Lake City, Utah. https://peer.asee.org/30911

Becker, K., Pourmohamadi, M., Abdellahi, S., Almeida, L., **Luo, Y.** & Gero, J. *Work in Progress: Quantifying the Differences Between Professional Expert Engineers and Engineering Students Designing: Empirical Foundations for Improved Engineering Education.* Proceedings of the 124th ASEE Annual Conference & Exposition, Columbus, Ohio, June 25-28, 2017.

Technical/Software Skills

- Statistical Analysis (SPSS, MS Excel, SAS)
- Computer Drafting and Modeling (SolidEdge/SolidWorks, AutoCAD)
- Engineering Related (Computations with Matlab, FEA with Nastran, Casca and franc2d)
- Programming (Matlab and Visual Basic)
- MS Office Suite (Excel, Word, Power Point)

Internship Experience

Quality Engineer Intern at Autoliv ASP, Inc. Summer 2015
Ogden, Utah

- Designed and prototyped machine parts in SolidWorks to accommodate for lean production
- Wrote a program in Visual Basic to automate data input at production cells

Leadership/Service

Member, American Society of Engineering Education (ASEE) 2016-2019
USU, Department of Engineering Education

- Represent ASEE student chapter at USU
- Organize events to foster engineering education

President, USU International Student Council 2015-2016
USU, Office of Global Engagement

- Promote international cultural diversity
- Represent international students and international student clubs

International Ambassador 2015-2016
USU, Office of Admissions

- International student recruitment
- Promote and represent USU colleges, campus, and student life

Executive Council and Member, Asian Student Association 2012 - 2014
USU, Access and Diversity