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Using a systemic skills model to build an effective 21st century workforce: factors that impact the ability to navigate complex systems

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factors that impact the ability to navigate complex systems

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ABSTRACT

The growth of technology and the proliferation of information made modern complex systems more fragile and vulnerable. As a result, competitive advantage is no longer achieved exclusively through strategic planning but by developing an influential cadre of technical people who can efficiently manage and navigate modern complex systems. The dissertation aims to provide educators, practitioners, and organizations with a model that helps to measure individuals' systems thinking skills, complex problem solving, personality traits, and the impacting demographic factors such as managerial and work experience, current occupation type, organizational ownership structure, and education level. The intent is to study how these skills, traits, and demographic factors can impact an individual's abilities in working effectively with modern complex systems. These skills and traits also enable individuals to display distinctive patterns of thoughts in developing solutions that address complex technical problems. The dissertation further provides strategies for the management and enhancement of technical individuals based on assessing their performance. The model consists of three established instruments: Systems Thinking Skills, Perceived Complex Problem-Solving (PCPS), and Myers-Briggs

Personality Type Indicator. These instruments are applied at the individual level to identify strengths and weak areas of improving an organization. In particular, PCPS is a researcher-developed instrument that captures the complex problem-solving perception of individuals. The different samples of the population for the dissertation comes from students and practitioners.

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CHAPTER I

INTRODUCTION

Modern systems are designed and develop to fulfill needs or provide solutions for bettering organizations and overcoming persistent challenges stemming from increasing complexity. However, systems and their derivative problems are not likely to be settled in the near future rather, and they are more likely to intensify in complexity. Perhaps, revolutions in technologies and the proliferation of information are indicative of the future, which must be dealt with by systems engineers. Thus, there is a need to employ a "systemic approach" to better manage and navigate these complex system problems (Alfaqiri et al., 2019; Hossain & Jaradat, 2018). In response, *Systems Engineering (SE)* has developed as a distinctive discipline to address these challenges and concerns by using a systemic approach to ensure that individual elements, sub-elements, and associated phenomena are functioning harmoniously in a given operational environment to achieve effective performance of the overall system.

A well-known research framework (that is, Creswell and Creswell's (2017) framework) is applied to develop the research plan of the dissertation. Creswell and Creswell (2017) introduce three major categories of research approaches, namely, qualitative, quantitative, and mixed methods approach. Researchers can select one of these approaches as the main framework of their study. A research approach consists of three interacting components, including philosophical worldview, research design, and research method, as shown in Figure 1.1. Creswell and Creswell (2017), in the glossary of their book, defined these components as follow:

1. *Research approaches*: "are plans and the procedures for research that span the decisions from broad assumptions to detailed methods of data collection and analysis. It involves the intersection of philosophical assumptions, designs, and specific methods." (p. 320).
2. *Research designs*: "are types of inquiry within qualitative, quantitative, and mixed methods approach that provide specific direction for procedures in a research study." (p. 320).
3. *Research methods*: involve the forms of data collection, analysis, and interpretation that researchers propose for their studies." (p. 321).
4. *Worldview*: is defined as "a basic set of beliefs that guide action" (Guba, 1990, p. 17).

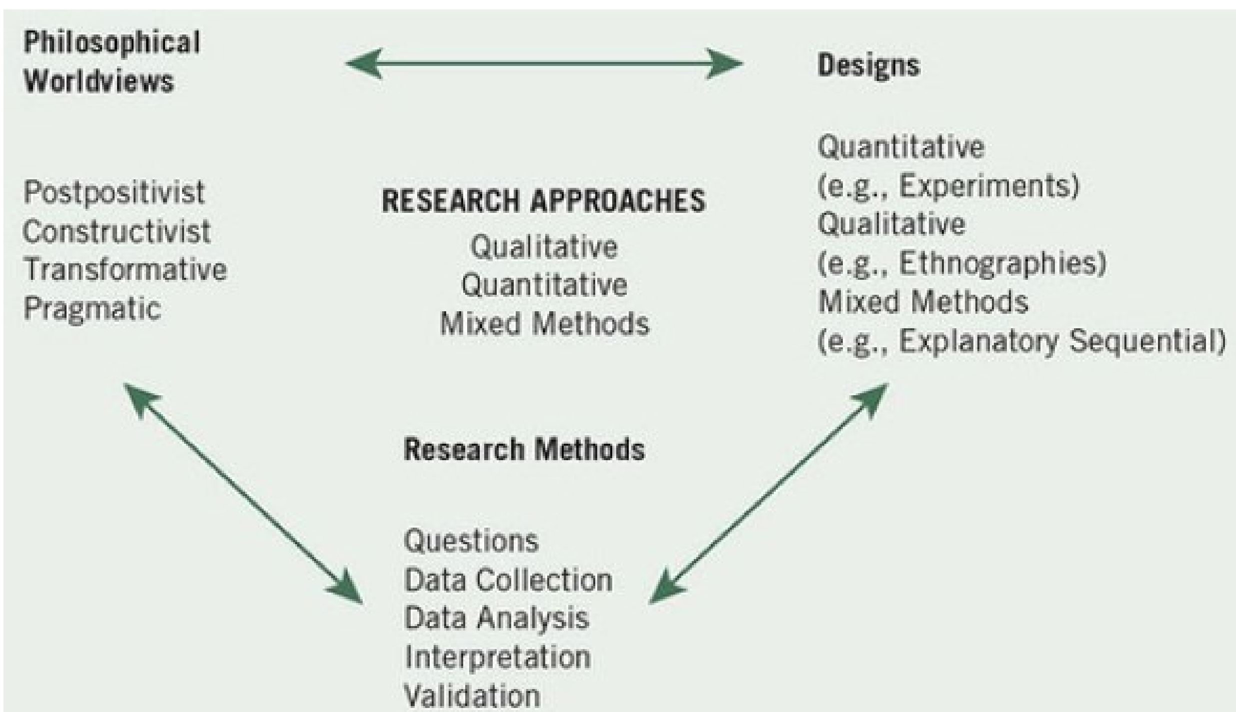

Figure 1.1 Research framework suggested by Creswell and Creswell (2017, Figure 1.1)

Three components of a research approach (worldview, design, and method) are interdependent and interactive and are defined for our study. The selected research approach of the dissertation is introduced as follows: 1) Brief introduction of what philosophical worldview is used for the dissertation, 2) explanation and application of the chosen research design, and 3) description of the research method's design.

1.1 Philosophical worldview

The definition of worldview for research is necessary because it shows the orientation and belief of a researcher in conducting a specific research approach. There are four primary worldviews in the literature called 'post-positivism,' 'constructivism,' 'transformative,' and 'pragmatism.' The pragmatism worldview is selected as the philosophical worldview of the dissertation. Rossman & Wilson (1985) defined the pragmatism worldview as worldview concentrate on research issue and question rather than a method. In other words, all possible methods and approaches can be used to explain the problem. This worldview is consistent with a mixed-method approach and gives us the freedom to utilize different methods and tools to explain the proposed theoretical model of the dissertation. The general research questions of the dissertation are, **(***1) To what extent are engineering students skilled at systems thinking? (Chapter II); (2) To what extent are Managers and students skilled at Perceived Complex Problem-Solving? (Chapter III); (3) What is the impact of personality Traits on the level of Systems Thinking Skills Preferences of systems engineers and engineering managers? (Chapter IV); (4) Can public and private sector managers be classified into two different groups regarding the level of Systems Thinking Skills? (Chapter V).* Both qualitative and quantitative analytical techniques such as structural equation modeling, scale development, machine learning, as well as qualitative and quantitative data from multi-source data collection, and case studies is used to explain the main goal of these studies in following chapters.

1.2 Research design strategies

According to Creswell and Creswell (2017), there are three main research designs, including quantitative, qualitative, and mixed methods. However, these three research approaches are not distinct and discrete from each other. As Creswell and Creswell (2017) said, "qualitative and quantitative approaches should not be viewed as rigid, distinct categories, opposites, or dichotomies. Instead, they represent different ends on a continuum (Creswell, 2015; Newman & Benz, 1998). A study *tends* to be more qualitative than quantitative or vice versa. Mixed methods research resides in the middle of this continuum because it incorporates elements of both qualitative and quantitative approaches" (p. 3).

A mixed-method research design, which is more toward a quantitative approach, is used in the dissertation. The qualitative design is applied to build the philosophical foundation from interdisciplinary pieces of literature, including personality traits from the psychology field, perceived complex problem-solving and performance factors from the management area, systems thinking (ST) from management and systems engineering disciplines and demographic factors from education literature. The qualitative research design is needed to link and explain the interrelationships of these different theoretical constructs and variables. The quantitative design is used extensively to test the relationship between different variables of the study. All the interrelationships (direct, moderation, mediation, control, and feedback effects) among constructs and variables are examined through correlational and causal analyses. As briefly explained, both quantitative and qualitative research designs are utilized in the dissertation, indicating the utilization of a mixed-method research design.

1.2.1 Research questions

Four main research questions with sub-questions are developed, which are commensurate with the four main goals of the dissertation in the purpose statement section. All these relationships are tested using correlational and causal analyses using different software packages.

1) To what extent are engineering students skilled at systems thinking? (Chapter II)

1a) Can engineering students be classified into two different groups of Holistic and Reductionist regarding the level of Systems Thinking Skills?

1b) Does the level of Systems Thinking of engineering students vary by their Academic Major of study?

2) To what extent are Managers and students skilled at Perceived Complex Problem-Solving? (Chapter III)

2a) What is the relationship between Perceived Complex Problem-Solving and Systems Thinking Skills of managers and students?

2b) Are there any differences between the two samples?

3) What is the impact of personality Traits on the level of Systems Thinking Skills Preferences of systems engineers and engineering managers? (Chapter IV)

3a) Does Education Level moderate this relationship?

3b) Does the Current Occupation type moderate this relationship?

3c) Does Managerial Experience moderate this relationship?

4) Can public and private sector managers be classified into two different groups regarding the level of Systems Thinking Skills? (Chapter V).

4a) Is there any differences between ST skills of public and private sector managers?

1.3 Design of research method

A mixed-method research design is selected for the dissertation; and, both qualitative and quantitative data are collected and analyzed to answer the research questions of the dissertation. In the following, different components of the dissertation's research method are discussed, which include survey design, the population of interest, data analysis, and results. Lastly, three dimensions of research design are reviewed.

1.3.1 Survey design

Survey design is used as the primary research method of the dissertation. The survey design provides a comprehensive description of the population samples of interest, which are students and practitioners, and also examines the interrelationship among all the study variables. Since almost most of the study variables (except demographic questions) are abstract and theoretical concepts from a human sample, the best approach to collect and test data is a survey design approach. The surveys are web-based, cross-sectional, multi-sources, and Likert scale; i.e., Likert scale (options are either a favorable or an unfavorable attitude toward the concept under study) or binary data are collected from two sources of students and practitioners by an online survey platform—Qualtrics. Moreover, where necessary, qualitative data like interviews from experts are conducted to provide data for the foundation and validation of the study.

1.3.2 The population and sample

The populations of interest for this dissertation are engineering students and practitioners (from certain disciplines such as systems engineering, engineering management, management, and related areas). Data are collected from students and practitioners of different races, nationalities, ages, gender, different education level, socioeconomic groups, and other demographic factors.

Various studies suggest a specific sample size for factor analysis and structural equation modeling. For example, Nunnally, Bernstein, and Berge (1967) suggested ten participants for each indicator, and the sample size of our study reach around 200 participants for each study depending on the number of indicators. Bentler and Chou (1987) recommended five cases per parameter estimation in the model. However, a sample size of two hundred should be adequate to perform all the analyses and maintain an acceptable power estimation and effect size for all the relationships of the study, and we have bigger sample sizes for our studies.

1.3.3 Data analysis

The dissertation variables mostly come from individuals' personality traits, behavioral preferences, and skills, which are theoretical and abstract concepts. As a result, appropriate scale development methods such as validation, exploratory and confirmatory factor analysis, multiple group analysis, power analysis, structural equation modeling are used to analyze the data. Three major software packages, namely, SPSS version 24.0, AMOS version 25.0, and R-studio version 4.0, are used to perform corresponding analyses. Various machine learning tools and techniques such as clustering, classification, and mixture modeling, regression analysis, etc., are used to investigate the dataset further using SPSS version 24.0, AMOS version 25.0, and R-studio version 4.0. As briefly explained, both quantitative and qualitative research methods are utilized in the dissertation, which shows a mixed-method research approach for the dissertation. All methods and models have some bias and error. The advantage of the mixed-method design is using both qualitative and quantitative methods to reduce the error and bias associated with each one of these methods.

1.3.4 Interpretation of research results

According to the recommendation of the '*Publication Manual of the American Psychological Association*' (APA, 2010), the study's results should be reported with a comprehensive description, significance testing, confidence interval, and effect size. For this study, the significance level associated with p-value < 0.05 (95% CI) along with the t-value is reported. Dependent on the type of path analysis, the result might interpret as a correlational, causal, interactional, meditated, or controlled relationship between variables. Positive and negative signs show the direction of the relationship (or strengthening/weakening for moderation analysis).

1.4 Research design's dimensions

The implications of the selected research design are discussed across three dimensions of theoretical, methodological, and practical.

1.4.1 The theoretical dimension of research design

As Kelloway (1998) stated, "theory can be thought of as an explanation of why variables are correlated (or not correlated)," which includes hypothesis testing of the proposed relationships between variables (p. 5). The purpose of the first study is to check to what extent engineering students are skilled at systems thinking? To properly explore the topic of improving students' system thinking, we must first develop a baseline of the students' current capability levels. Additionally, we are interested in investigating the variation of systems thinking skills by academic majors of engineering study. In conclusion, the first study discusses the capability of engineering students' systems thinking skills.

The goal of the second research is to test a newly researcher-developed instrument called, Perceived Complex Problem-Solving instrument. In other words, the 'construct validity' for the

Perceived Complex Problem-Solving instrument is discussed. For validation, exploratory and confirmatory factor analyses are conducted to show the new instrument is valid and reliable. In addition to factor analysis, ‘nomological validity’ is another critical part of construct validity. The newly developed scales need to be tested through nomological validity, as well as factor analysis. As Peter (1981) noted, “nomological validation is primarily ‘external’ and entails investigating both the theoretical relationship between different constructs and the empirical relationship between measures of those different constructs.” (p. 135). For this purpose, the connection between the newly developed instrument, called “Perceived Complex Problem-Solving,” and an established ST Skills instrument is checked. Therefore, the second research’s goal is assigned to develop construct validity and nomological validity for the Perceived Complex Problem-Solving instrument.

The aim of the third study is to test the relationship between systems thinking skills and personality traits of systems engineers and engineering managers while moderating the education level, managerial experience, and current occupation type. In other words, we are interested to know what is the impact of practitioners’ personality traits on their level of systems thinking skills. For achieving this purpose, we investigate the relationship between all variables of this study simultaneously. In sum, the third goal of the research is devoted to investigating the linkage between personality characteristics, demographic factors, and the level of systems thinking of practitioners.

The objective of the fourth study is related to investigate the level of systems thinking skills of senior (with more than 21 years of experience) public and private sector managers and whether the organizational ownership structure has an impact on the level of systemic thinking of senior managers. In sum, the fourth study shows the differences in thinking characteristics and skills of senior public managers in comparison with private senior managers.

1.4.2 The methodological dimension of research design

Since almost most of the study variables are abstract and theoretical concepts from a human sample, the best approach to collect and test the data is survey design research. In order to investigate and address the research objectives of the dissertation, web-based, cross-sectional, multi-source, Likert scale (options are either a favorable or an unfavorable attitude toward the concept under study) survey designs are used as the primary design of the research method. The survey design provides a comprehensive description of the populations of interest, which are students and practitioners, and also examines the interrelationship among all the study variables.

Initially, all the scales and measures pass a thorough validation process. The central purpose of the validation process is to make sure the theoretical model of each study is valid and reliable. A theoretical model that lacks adequate validity and reliability is the "garbage in garbage out" model (Churchill, 1979, p. 64). After accomplishing the validation process for the theoretical models of the dissertation, we prove that the theoretical model does have 'construct validity,' meaning it can measure what supposed to measure. In other words, the theoretical model is valid and reliable, and the hypotheses of the study can be investigated through the theoretical model. To test the hypotheses of the study, Structural Equation Modeling (SEM), which is a powerful package of analytical tools, is utilized. This analytical package (SEM) can conduct many different analyses including, 1) path coefficient and full structural analysis, 2) mediation, moderation, moderated mediation, and mediated moderation tests, 3) multiple group analysis, 4) bootstrapping, 5) clustering and classification of latent variables, 5) common method bias, 6) all the analysis related to formative and higher-order constructs, 7) latent growth curve, 8) mixture modeling, 9) handling missing data and censored data using Monte Carlo Markov Chain distribution, 10) power analysis, and 11) handling the non-recursive models. Most of these analyses are used to discover different aspects of the proposed theoretical model of the dissertation, and this approach is consistent with the pragmatism worldview as the research's philosophical worldview.

Additionally, SEM using AMOS version 25.0 has many advantages in analyzing the survey data. Structural Equation Modeling (SEM) enables us 1) to explain the variance of all study variables at the same time (not step by step and independent from each other); 2) to account for measurement error for each part of the model; 3) to have multiple dependent variables as well as processing/hidden variables such as moderators and mediators; 4) to build a complex theoretical map the shows the big picture of the whole research; 5) to use different estimation methods such as maximum likelihood, general least square, asymptotically assumption-free and other estimations; 6) to utilize confirmatory factor analysis to conduct the scales validations prior to hypothesis testing; 7) to have comprehensive model-fit indexes that help us to conduct the construct validity, discriminant validity, and convergent validity for the proposed theoretical model; and finally, 8) to conduct advanced techniques mixture modeling using Bayesian latent class analysis, post-hoc power analysis, and other techniques. All these features and techniques are used to analyze the dataset rigorously to generate valid and reliable theories and outputs.

In addition to using a powerful analytical package, some specific designs in the survey are used to decrease the non-sampling bias. Non-sampling bias is a fatal flaw in survey research design that casts doubt on the validity of research findings. These specific designs are: 1) Several demographic variables are considered in the survey design. These variables are used as control and moderator variables to explain the inter-relationship among study variables. By having more demographic information, we can reduce the systematic error by identifying the non-respondents bias for the data collection. 2) Reverse worded questions, attention check questions, and the survey duration for respondents in identifying the respondent misconduct in the data collection process. 3) The formative higher-order construct (instead of a reflective one) is used to capture the level of systemic thinking of students. The formative higher-order construct is a unique and advanced design for measuring different dimensions of systemic thinking as an *index (*for more information about formative construct, see Bollen and Lennox's (1991) study). This study is the *first study* that uses a higher-order formative construct to capture the level of systems thinking and complex problem-solving in the literature.

1.4.3 The practical dimension of research design

In the practical dimension, the research design enables us to understand the impact of perception, characteristics, and behavior of practitioners and students. This research advances the body of knowledge in different disciplines such as systems engineering, engineering management, management science, education, psychology, and organizational behavior. The most important contribution of this research will be a better understanding of practitioners' and students' soft skills such as systems thinking skills and perceived complex problem-solving and what impacts them, including personality traits, demographic factors, among others. This contribution can help organizations, human resource specialists, educators, teachers, college authorities, and other involved parties to understand practitioners' and students' behavior and individual differences better; and, consequently, more efficiently train and guide them. This research design is able to explain why and how the study variables (including ST skills preferences, perceived complex problem-solving, personality traits, demographic factors, and others) differ across the practitioners' and students' samples. In other words, what variables make practitioners and students more effective and well-performed in career and academic tenure, respectively. A thorough review of the National Science Foundation (NSF) awarded projects related to education and industry (career and skills development) setting shows that systems thinking and complex problem-solving can play a vital role in learning and academic performance of students and job performance, career development, and career success of the practitioners.

Although there are some systems thinking tools available in the literature, the validity, and reliability, and functionality of these systems thinking tools are not adequately developed. In other words, it is hard to accept the outputs of these systems thinking tools are valid and reliable without observing enough information regarding the reliability, construct, nomological, trait, criterion, and content validity of these scales. Additionally, there is no survey instrument in extent literature to measure the perceived complex problem-solving of individuals. One of the main contributions of the dissertation is developing and validating a new instrument to measure the complex problem-solving perception of individuals--practitioners or students. A study that shows the thorough validation of systems thinking skills instruments will be another practical contribution of this research.

Another contribution of this research is the assessment of the complex problem-solving of students in the education domain and practitioners in the industry domain. In author knowledge, there is no study that investigates the impact of systems thinking skills of individuals on their complex problem-solving perception for students' sample in an education setting and practitioners' sample in industry. As a result, this contribution advances the body of knowledge in education discipline and practitioners' sample in the industry by finding a new factor that impacts their performance.

Another practical contribution of this research is to identify the different characteristics of the sample under study and how these characteristics impact the variables of the study, such as ST skills, complex problem-solving, and others. The demographic variables contain essential information about the populations of interest__ practitioners and students. However, researchers typically do not pay adequate attention to the importance of these variables. In this study, we try to include all the impacting demographic variables relevant to soft skills and to explain their effect on other study variables. This contribution can help us to find what demographic factors are more influential for each category of the sample, which enables us to provide effective implications for the sample of interest. For example, we can compare the systems thinking of adult female students from the middle class against their counterparts and also contrast the level of their ST skill preferences of each group. If two groups have different systemic level which makes a group performs better than the other, educators and college authorities are able to identify this challenge and plan for an adequate curriculum which does not overperform a group over the other.

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CHAPTER II

TOWARD A BETTER ASSESSMENT OF ENGINEERING STUDENTS' SYSTEMS THINKING ABILITY

2.1 Abstract

- **Background** - The need to have a more holistic formation of engineering students is a challenge for the current American higher education system. The existing engineering formation field and funding agencies, such as the National Science Foundation, emphasize the need to prepare future engineers to be well trained for the evolving complex multidisciplinary demands of the global labor market. The global labor market needs a skillset that can deal with social-technical problem dimensions.
- **Purpose/Hypothesis** - To what extent are engineering students skilled at systems thinking? To properly explore the topic of improving students' system thinking, we must first develop a baseline of the students' current capability levels.
- **Design/Method** – A total of 503 engineering students from 8 departments and 12 majors across the College of Engineering participated in the survey. In this study, we used different analytical methods (i.e., Bayesian latent class analysis) to assess the current systems thinking (ST) ability of college engineering students.
- **Results** - The assessment includes an ST profile for each participant and a total aggregate score of ST for each student. This study also clustered students based on their ST skill

scores. Each cluster shows the difference between the ST ability of students across twelve majors of engineering.

- **Conclusions -** The main findings of the study suggest that 2- cluster analysis, which is more holistic thinkers and more reductionist thinkers, is the best fit for the current sample of the study. Revisit the enringing education curriculum is one of the recommendations this study provided based on the findings of the results.

Keywords: systems thinking, complex systems, engineering education, college students, clustering, engineering formation.

2.2 Introduction and Motivation

The World Economic Forum (2016) published "The Future of Jobs" report that identifies and defines the important workforce skills needed in a complex workplace environment. The report identifies complex problem solving and critical/systems thinking skills as the important skills for the next five years, outpacing the need for other skills such as people management, emotional intelligence, negotiation, and cognitive flexibility. This need is apparent when considering the increasing complexities experienced by organizations (Boardman and Sauser, 2008). Organizational practitioners, including engineers, managers, and decision-makers, must address increasingly complex systems and their associated problems. Organizations dealing with complex systems face a "new normal" in which challenges are marked by increasing levels of challenging attributes, including uncertainty, ambiguity, emergence, complexity, and interdependence (Ackoff, 1995; Boardman and Sauser, 2008; Keating, 2008). These challenges are likely to escalate as we grapple with the interdisciplinary system problems of the 21st century, blurring the lines between technical, social, organizational, managerial, and policy considerations. In response to these challenges, organizations are focusing on integrating increasingly interdependent operations, processes, and systems that must work together to achieve performance beyond that attainable by individual systems (Jaradat, 2015; Jaradat and Keating, 2016; Jaradat, Keating, and Bradley, 2017). Effective integration of increasingly interconnected complex systems across the holistic range of socio-technical issues continues to confound the achievement of higher performance levels. Thus, there is a corresponding need to build a cadre of qualified individuals who can take a more holistic, "systemic" approach in dealing with complex system problems.

One such systemic approach is represented by the Systems Thinking (ST) framework (Flood and Carson, 2013; Jaradat, 2015; Frank, 2006; Senge, 2006). ST is a way of framing how we see, interpret, make sense of, and respond to the complex world we encounter daily. ST is a capability of professionals that allows them to deal with the complexities of modern systems. ST applies the principles of a holistic approach, which allows the interaction of the parts that is more important than the parts themselves (Flood and Carson, 1993). As such, ST takes a holistic approach to understanding complex systems. Applying this holistic, systems-based thinking to the complex work environments encountered in today's organizations offers a solution toward addressing the challenging attributes of uncertainty, ambiguity, emergence, complexity, and interdependence.

One group of professionals who could most benefit from ST are engineers. Engineers potentially deal with systems in different aspects of their professional career and experience first-hand the ill effects of deficiently designed, executed, and evolved systems, such as poor service, underperformance, wasted resources, among others (Honour, 2004). The present study examined the ST ability of engineering undergraduate students across 12 engineering majors. The goal was to determine the degree to which these budding engineers had ST ability in the absence of formal training. Ultimately, this measure could serve as a baseline to inform future educational practices designed to increase ST ability.

2.3 Background

The philosophy of ST is not new; its origins can be traced to early Chinese society and can be found in the work of I Ching (around 400 B.C.). Aristotle (384-332 B.C.) introduced the holistic thinking paradigm, which, similar to ST, suggests that the whole is more than the sum of the parts. Since then, many perspectives, taxonomies, definitions, and implementations have flourished in describing ST. Jackson (2003) used “applied ST” to show the applicability of ST via tools and techniques. Although some research has examined ST in terms of the theory itself, most ST and critical thinking research has been focused on training and implementation of ST in a variety of educational domains (Bloom, 1956; Stave and Hopper, 2007; Sweeney and Sterman, 2000), including engineering education (Frank, 2000, 2006; Gorod, Sauser, and Boardman, 2008; Ossimitz, 2000), systems engineering (Hossain et al., 2019a, 2019b; Jaradat et al., 2017), engineering management (Jaradat et al., 2019; Nagahi et al., 2020), students’ learning (Cai and Cheung, 2019; Chen, Tolmie, and Wang, 2017; Dunne, 2015; Hadar, 2009; Kamei and Pavlovic, 2021; Kwan and Wong, 2015; Larsson, 2017) management and operation research (Ackof, 1994, 1995; Checkland, 1999; Churchman, 1979; Deming, 1982; Drucker, 2012a, 2012b; Senge, 1991, 2004), and system of systems engineering (Katina et al., 2014; Keating, 2008; Keating et al., 2003).

Researchers have recognized the need to apply a systemic perspective to successfully examine complex system problems (Jackson, 2003; Checkland, 1999; Keating et al., 2003; Katina et al., 2014; Senge, 1991; Maier, 2005). Based on research ranging from the 1980s to 2018 (Ackof, 1994, 1995; Checkland, 1981, 1999; Churchman, 1979; Deming, 1982; Drucker, 2012a, 2012b; Frank, 2006; Gorod, Sauser, and Boardman, 2008; Hossain, Jaradat, Hamilton, Keating, and Goerger, 2019a, Hossain, Nagahi, Jaradat, and Keating, 2019b; Jaradat et al., 2017; Keating et al., 2003; Lawrence, Hossain, Nagahi, and Jaradat, 2019; Nagahi et al., 2020; Senge, 1991, 2006), the need for a more holistic perspective, rooted in higher-level ST, has been identified as providing a congruent frame of reference for engaging complex systems and their problems.

Engineers are professionals who deal with complex systems in their daily work (Honour, 2004). Researchers have long argued the need for engineers to have what is often referred to as the "Fifth Discipline" of organizational management (Senge, 2006). Frank (2006) expanded the concept of organizational management into the Capacity for Engineering Systems Thinking (CEST), which is a competency model specific for engineers. The CEST framework includes the need for engineers to understand systems synergy, interconnections, and implications of change, and posits that engineers must possess these skills to succeed. The future (and oftentimes current) workforce demands that engineers be armed with these types of skills (Hämäläinen, Saarinen, and Törmänen, 2018; Kordova, Ribnikov, and Frank, 2015). Engineers, by definition, are challenged to create order out of ill-designed systems, and this challenge requires attention to the system as a whole while also focusing on many dependent sub-systems. Failures in complex systems can result from non-technical as well as technical elements and can be related to organizational and individual issues where individuals are an essential contributor to the failure. These failures can be classified as having socio-technical aspects stemming from both technical and social elements as well as interactions between those elements (Jaradat et al., 2017; Katina, Keating, and Jaradat, 2014; Frank, 2006). Engineers are trained to deal with these types of complex systems, especially those that have a combination of both technical (technology) and non-technical (culture, human/social, policy, politics, power, and others) aspects (Clegg, 2000; Checkland, 1981). However, the attempt to manage and understand increasingly complex systems requires engineers with a commensurate set of skills to formulate the problem domain holistically, including both the technical as well as the full spectrum of political, cultural, human, and managerial knowledge dimensions. Appreciation of this holistic frame of reference is necessary to the development of rigorous solutions to more effectively address complex multidimensional problems.

The need to engage in more holistic systems thinking for the engineering profession has been identified as a necessary skill to enable engineers to deal with increasingly complex multidisciplinary problems (Beder, 1999; Davidz and Nightingale, 2008; Wasson, 2015). Additionally, there is recognition of the value of immersion in educating engineering students in systems thinking at the very formative stages of their preparation for entry into the profession (Nagel, Gipson, & Ogundipe, 2017; Abdulwahed, Balid, Hasna, & Pokharel, 2013; Yurtseven & Buchanan, 2016). Conventionally, the preparation of engineers has involved development in specific disciplines through the delivery of specialized coursework. However, passing courses is far from a guarantee of professional mastery (Schachterle, 1999), and focusing only on technical proficiency cannot match the engineering requirements demanded by the future job market. What is required is are engineers who can "think broadly across disciplines and consider the human dimensions that are at the heart of every design challenge" are needed to satisfy the global intensely competitive environment in the 21st century (Grasso & Martinelli, 2007, p. 58). To meet the challenge, an emphasis on more holistic thinking modes should be involved and accentuated in future engineers' training. Future research will focus on the training of engineers toward the development of ST ability; however, what is less understood is the degree to which engineering students possess ST ability. “Soft” skills are complementary to “hard” skills, which are traditionally taught through courses (ASGE Bariatric Endoscopy Task Force, 2015). Aly (2014) introduced five “soft” skills that engineers should master: communication, creativity, adaptability, collaboration, and leadership. These skills could be enhanced through ST training. However, to create a curriculum to do ST training as part of engineering education, it is important to understand the ST ability of the typical engineering student. Therefore, the current study has been designed to shed more light on engineering students’ holistic formation in different majors of engineering studies in advance of formal ST training.

The purpose of the current study is to measure the current level of the systems thinking (ST) ability of engineering students. ST ability was measured using the Systems Thinking Questionnaire (STQ; Jaradat, 2015; Jaradat et al., 2017). Students were undergraduate engineering majors enrolled in classes in the College of Engineering at a public state university voluntarily completed the STQ as a measure of their current ST ability. Data will be reported both in terms of their overall ST ability, as well as their scores on the seven ST ability dimensions.

2.4 Method

2.4.1 Design and Participants

Participants were students who were engineering majors from 8 departments and 12 majors across the College of Engineering who were currently registered for engineering classes. They were contacted via email to request their participation. Participation was voluntary, and responses could not identify any participant. Two hundred and eighteen Amazon gift cards were awarded to participants who provided their contact information through a separate portal and completed all the surveys.

A total of 503 students participated in our survey. Survey responses were only included if participants completed the STQ, which eliminated 172 participants from inclusion in subsequent analyses. An additional 6 participants were eliminated from inclusion based on misconduct in their responses (i.e., not following instructions). After applying these criteria, 325 complete responses were used for analysis.

The 325 engineering students who took the survey were registered for the courses in the data collection period. They had an average age of 20.9 years with a standard deviation of 2.2 years. Sixty-five percent of engineering students were male, around 33% female, and around 2% did not disclose their gender. Moreover, 73% of them were Caucasian, 9.5% African-American, 6.8% Asian, 2.8% Hispanic, 0.9% Middle-Eastern, 2.8% multi-racial, and remaining (4.3%) preferred not to disclose their ethnicity. Fourteen and a half percent of engineering students had a Cumulative Grade Point Average (CGPA) of 4.00, 69.5% had CGPA equal or more than 3.00 and less than 4.00, and 16% had CGPA below 3.00. College of Engineering at Mississippi State University composed of 12 majors of engineering studies within eight departments. Engineering students represented in the data are listed in Table 2.1, along with their proportions.

Table 2.1 Frequency Percentage of Engineering Students by Academic Major

Major of Engineering Study	**Frequency**	**Percent**
Aerospace Engineering	28	8.6
Biological Engineering	8	2.5
Biomedical Engineering	24	7.4
Chemical Engineering	45	13.8
Civil Engineering	36	11.1
Computer Engineering	19	5.8
Computer Science	26	8.0
Electrical Engineering	23	7.1
Industrial Engineering	23	7.1
Mechanical Engineering	79	24.3
Petroleum Engineering	5	1.5
Software Engineering	9	2.8
Total	**325**	**100.0**

2.4.2 Materials

The STQ was administered to all participants. The 39-item STQ was designed to measure an individual's ability for ST when dealing with complex system problems (Jaradat, 2015; Jaradat et al., 2017; Jaradat et al., 2019). These complex problems are not restrictive and can cross different fields such as education, transportation, energy, healthcare, among others. The STQ instrument examines seven dimensions of ST, listed in Table 2.2, using a 39-question web-based survey instrument. The STQ instrument was developed using a mixed-method approach to gather both qualitative and quantitative data for analysis and is reliable (Cronbach $\alpha = 0.90$; Jaradat et al., 2019, p. 65).

Table 2.2 Definition of Systems Thinking Ability Dimensions, Range of Values on STQ (Jaradat et al., 2017)

Dimension	Less Systemic (holistic)	More Systemic (holistic)
Level of Complexity: Comfort with multidimensional problems and limited system understanding	**Simplicity (S)**: Avoid uncertainty, work on linear problems, prefer the best solution, and prefer small-scale problems.	**Complexity (C)**: Expect uncertainty, work on multidimensional problems, prefer a working solution, and explore the surrounding environment.
Level of Autonomy: Balance between local-level autonomy versus system integration	**Autonomy (A)**: Preserve local autonomy, tend more to an independent decision and local performance level.	**Integration (G)**: Preserve global integration, tend more to a dependent decision and global performance.
Level of Interaction: Interconnectedness in coordination and communication among multiple systems	**Isolation (N)**: Inclined to local interaction, follow a detailed plan, prefer to work individually, enjoy working in small systems, and interested more in cause-effect solution.	**Interconnectivity (I)**: Inclined to global interactions, follow a general plan, work within a team, and interested less in identifiable cause-effect relationships
Level of Change: Comfort with rapidly shifting systems and situations	**Resistance to Change (V)**: Prefer taking few perspectives into consideration, over-specify requirements, focus more on internal forces, like short-range plans, tend to settle things, and work best in a stable environment.	**Tolerant of Change (Y)**: Prefer taking multiple perspectives into consideration, underspecify requirements, focus more on external forces, like long-range plans, keep options open, and work best in changing environment.
Level of Uncertainty: Acceptance of unpredictable situations with limited control	**Stability (T)**: Prepare detailed plans beforehand, focus on the details, uncomfortable with uncertainty, believe the work environment is under control, and enjoy objectivity and technical problems.	**Emergence (E)**: React to situations as they occur, focus on the whole, comfortable with uncertainty, believe the work environment is difficult to control, enjoy subjectivity and non-technical problems.
Level of Hierarchical View: Understanding system behavior at the whole versus part level	**Reductionism (R)**: Focus on particulars, prefer analyzing the parts for better performance.	**Holism (H)**: Focus on the whole, interested more in the big picture, interested in concepts and abstract meaning of ideas.
Level of Flexibility: Accommodation of change or modifications in systems or approach	**Rigidity (D)**: Prefer not to change, like a determined plan, open to new ideas, motivated by routine.	**Flexibility (F)**: Accommodating to change, like a flexible plan, open to new ideas, and unmotivated by routine.

Each question on the STQ is binary and forced-choice; participants choose their preferred response. For example, one item asked, “Are you most comfortable developing (a) a detailed plan or (b) a general plan?” as a way of measuring the fifth level, uncertainty. Each level is assessed by presenting dichotomous choices that represented pairs of opposite underlying traits. The first pair (simplicity vs. complexity) assesses the level of complexity (C-S), an individual’s comfort zone for engaging complex system problems. The second pair (autonomy vs. integration) assesses the level of autonomy (G-A), an individual’s inclination in dealing with the integration of multiple systems or internal systems. For instance, (G)-type systems thinkers focus more on applying a global perspective and treat the system as an integrated unit. The third pair (isolation vs. interconnectivity) assesses the level of interaction (I-N) or what type of scale with which an individual would choose to work. The fourth pair (resistant or tolerant to change) assesses the level of change (Y-V) or an individual’s propensity to accept change. The fifth pair (stability vs. emergence) assesses the level of uncertainty (E-T), described as an individual’s preference in making decisions with incomplete knowledge. The sixth pair (reductionism vs. holism) assesses the level of hierarchical view (H-R) and indicates the way the individual approaches problems within a larger complex system. An individual whose answers fall into the (H)-category is probably more interested in applying big picture concepts and ideas. Conversely, (R)-type systems thinkers prefer to focus on particulars and details. Finally, the seventh pair (rigidity vs. flexibility) assesses the level of flexibility (F-D), an individual’s preference for altering plans.

2.4.3 Procedure

Participants were provided with a link to a Qualtrics survey (Qualtrics, Provo, UT, 2020) via an email requesting their participation. The survey opened with a consent form, letting students know that the study was voluntary, confidential, and about compensation for their time (the procedures and materials for this study were reviewed and approved by the University Institutional Review Board). Consent was provided by continuing the survey. Participants answered the 39 questions on the STQ by selecting one of the two options by clicking a radio button with their mouse. Following the STQ, participants completed some other tasks, including a demographic questionnaire. Those results are not relevant to the current research question and will not be presented here, except for the basic demographic information reported in section 3.1.

2.4.4 Analytical methods

2.4.4.1 Bayesian Latent class analysis (BLCA)

Latent class analysis (LCA) is a person-centered statistical method that groups individuals into classes based on responses that exhibit similar patterns (Liu et al., 2017). LCA is similar to typical Cluster Analysis (CA) in that both methods cluster individuals homogeneously (Porcu & Giambona, 2017). However, LCA compensates for two major drawbacks associated with CA: (1) the absence of an underlying statistical model and (2) the inability to provide a probability for an individual who belongs to a particular class (Porcu & Giambona, 2017). BLCA can be performed as a clustering technique without pre-defined groups, which is an unsupervised learning approach. "BLCA is a powerful method for analyzing the relationships among manifest data when some variables are unobserved; Additionally, BLCA does not rely on traditional modeling assumptions (e.g., linear relationship, normal distribution, homogeneity) and is, therefore, less prone to biases; and also the relationship between the latent classes and external variables can be assessed simultaneously" (Costa, Santos, Cunha, Palha, & Sousa, 2013, p. 4). In addition to cluster membership, BLCA by AMOS provides a probability of membership and probability distribution for each individual case, which helps in better interpretation of clustering results.

2.4.4.2 Kmeans

Kmeans clustering is a popular unsupervised learning technique utilized in data mining. The Kmeans clustering's function related to the detection of a number *k* of clusters in a dataset consisted of *n* observations. In the Kmeans algorithm, each cluster is defined by a centroid-- a point at the center of the cluster. The logic behind this method is to identify *k* number of centroids and assign the variables to the closest cluster utilizing the Euclidean distance. The next step is composed of calculating the average values of all variables for each centroid. Each average value evolves into the new value of the centroid. This process iterates until the centroid values became almost constant. The intent of this technique is to keep the centroids small.

2.4.4.3 TwoStep

The SPSS TwoStep Cluster is an analysis of the automatic clustering algorithm developed to analyze large datasets that are consisted of continuous and categorical measures. This method represents an extension of the model-based distance measure established by Banfield and Raftery (1993). It is based on a likelihood distance measure that considers the data variables to be independent variables. If the data is composed of continuous variables, which is the case for the current data, each continuous variable is considered to have a Gaussian distribution. The TwoStep Cluster, as indicated in its name, consists of two consecutive steps. In the first step, the data is decomposed into many small clusters. This step is known as the cluster features Tree. The second step consists of grouping the pre-clustered small data into the desired number of clusters using an agglomerative clustering algorithm. One more advantage of this method is that it can be used to identify the adequate number of the clusters in case the number is unknown using "Schwarz's Bayesian Criterion (BIC)" or "Akaike Information Criterion (AIC)" comparison (SPSS, 2016; TwoStep Cluster Analysis sub-section). The results of the analysis are usually precise, scalable, and fast in terms of performance (SPSS, 2016). The clustering process is beneficial in the sense that the data can be grouped. For instance, retail stores use the clustering method to describe their customers and classify them into groups. This would help retail stores to increase their profits and satisfy each customer category.

2.4.5 Scoring the STQ

The STQ produces a score sheet that captures an individual's level of systems thinking ability: the ST profile. The outcome of the STQ consists of scored scales to measure the seven dimensions. These 14 labels (2 opposite extremes for each of the seven dimensions) reflect an individual's level of ST in engaging complex system problems. The ST profile identifies an individual's ability to engage with complex system problems. Table 2.3 shows a sample score calculation for one individual.

After each individual's ST scores pertaining to seven dimensions were computed, the mean and standard deviation for the entire sample were calculated and are summarized in the two last columns of Table 2.4. Additionally, for each dimension, the scale extremity that was chosen more often became the letter in the ST profile. In other words, a score of 50% and higher in each dimension was associated with a more systemic letter and vice versa. This method created seven pairs of letters associated with seven dimensions of ST ability for each participant. Table 2.4 shows the frequency of each of seven ST pairs among the sample of the population (that is, 325 engineering students). In three dimensions out of seven dimensions—Interaction, Complexity, and Flexibility—the majority of engineering students had more systemic profiles. However, in the other four dimensions—Autonomy, Change, Uncertainty, and Hierarchical View—the majority of engineering students had less systemic profiles.

Table 2.3 A Sample of ST Score Calculation for one Participant.

Dimension	**ST Ability Questionnaire**	**More Systemic Responses**	**Dimension Score (%)**	**Profile Designation**
Level of Complexity	6	2	33.3	S
Level of Autonomy	5	0	0.0	A
Level of Interaction	6	6	100.0	I
Level of Change	6	1	16.7	V
Level of Uncertainty	6	2	33.3	T
Level of Hierarchical View	5	1	20.0	R
Level of Flexibility	5	3	60.0	F
Total aggregate ST score [a]			**38.5**	**SAIVTRF**

[a] The sum of more systemic responses divided by 39 multiply by 100.

Table 2.4 Frequency of Each of Seven ST Pairs among the Sample of the Population.

Dimension	ST Profiles Frequency				Continuous ST Score	
	More Systemic Responses		***Less Systemic Responses***		[0 to 100][a]	
	Profile Designation[b]	Frequency %	Profile Designation[b]	Frequency %	M	*SD*
Level of Interaction	N	52.3%	I	47.7%	45.7	23.5
Level of Autonomy	A	32.3%	G	67.7%	40.2	23.0
Level of Change	V	42.2%	Y	57.8%	39.9	16.2
Level of Uncertainty	T	37.5%	E	62.5%	36.0	20.5
Level of Complexity	C	56.0%	S	44.0%	46.8	23.4
Level of Hierarchical View	R	23.4%	H	76.6%	37.2	20.5
Level of Flexibility	D	68.6%	F	31.4%	62.8	24.3

[a] A higher score is corresponding to more systemic. [b] Profile designations have been defined in Table 2.2.

2.5 Results

2.5.1 Total Aggregate ST Score

The mean of total aggregate ST score across all engineering students was 43.87%, with a standard deviation of 11.10. Total aggregate ST scores of engineering students in the sample of the population ranged from 10.30 (more toward less systemic extreme) to 79.50 (more toward the systemic extreme). The median of total aggregate ST scores of engineering students shows that 50 percent of the sample of the population scored less than 43.60 and more reductionist. Figure 2.1 presents the frequency of total aggregate ST scores across the sample of the population. Based on total aggregate ST scores, the majority of engineering students scored from 33.0 to 55.0.

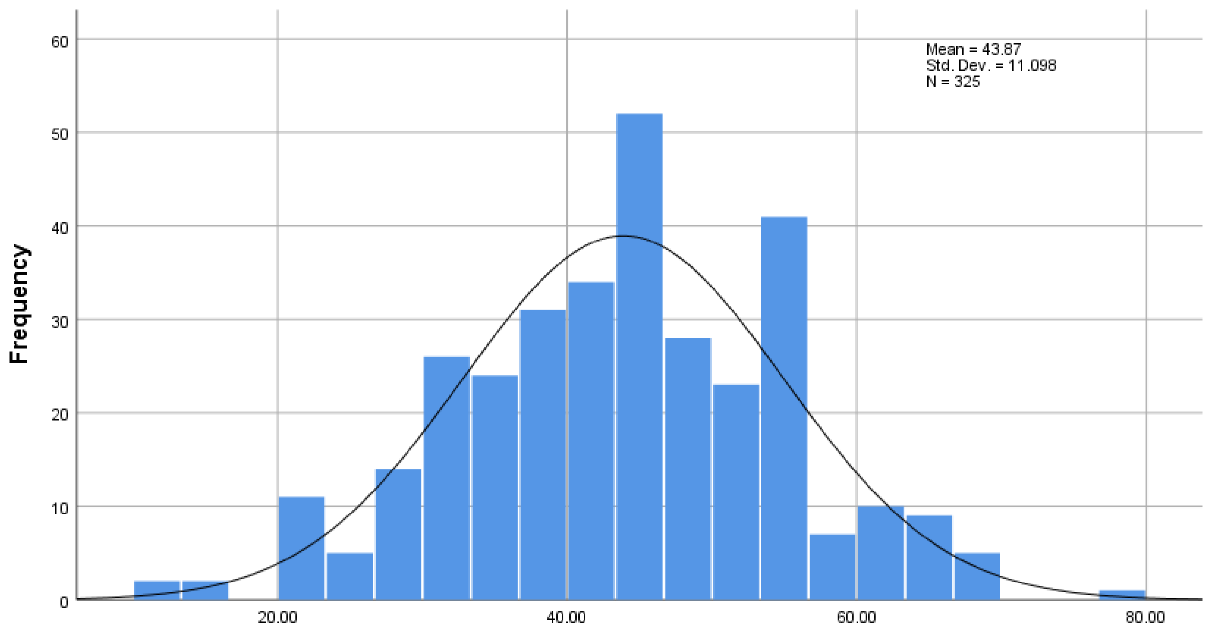


Figure 2.1 Frequency of Total Aggregate ST Scores of Engineering Students (n=325)

2.5.2 Clustering engineering students by ST score

To better understand the ST formation of engineering students, clustering methods were used. BLCA clustering was used as the primary clustering method. Then, the BLCA results were compared with the results of two established clustering methods: Kmeans and TwoStep. Figure 2.2 presents the theoretical framework of the current study.

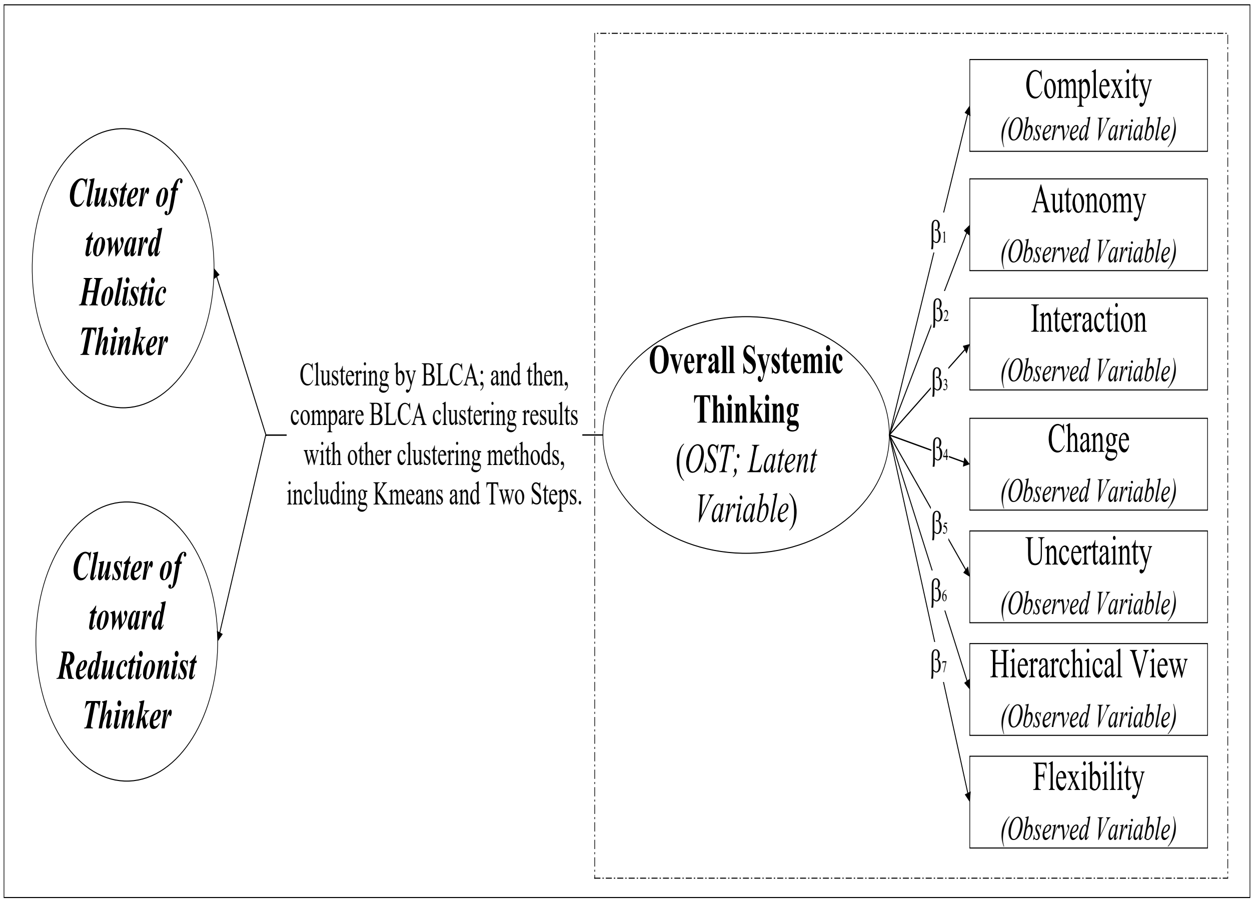


Figure 2.2 The Theoretical Model of the First Study

2.5.2.1 Bayesian Latent Class Analysis (BLCA)

In this study, overall systemic thinking (OST) is designed as a latent/unobserved dependent variable, and the seven ST ability scores of the individuals are served as the observed variables. We measured OST through seven dimensions of the STQ instrument, as shown in Figure 2.2. BLCA clustered individuals' OST based on the observed ST scores. OST indicates the degree to which individuals think systemically. The intent was to cluster students based on their OST. Because clustering is an unsupervised learning technique, we do not need to pre-define the number of clusters. BLCA was able to test a different number of clusters to find the best clustering solution. The spectrum of BLCA clustering was between two extremes: low OST and high OST. BLCA assigned each data point to distinct latent clusters based on the observed continuous variables, which were the seven ST dimension scores (Muthén and Muthén, 2000).

Consistent with Costa and colleagues (2013), AMOS software version 24.0 was used to perform BLCA with Markov chain Monte Carlo simulation to cluster students based on their OST. The dataset consisting of the seven ST dimension scores of all 325 students was fed to the BLCA to find the best clustering solution for the data. All solutions from 2-cluster to 8-cluster were tested through approximately 60,000 resamplings and compared against all fit indices provided by AMOS, including the Gelman and colleagues (2004) convergence criteria of < 1.002 and Posterior Predictive P-value (PPP) of 0.50 as well as Nagin's (2005) criterion of posterior probabilities of correct class assignment > 0.70. The 2-cluster solution resulted in the best convergence statistic (CS) of 1.0003 ("CS, as it approaches 1.0000 there is no much more precision to be gained" (Costa et al., 2013, p. 2)), satisfying the Gelman and colleagues (2004) convergence criteria of < 1.002, and the good PPP of 0.59 among other solutions. For this solution, 283 out of 325 (around 87.1 percent clustering accuracy) cases correctly classified; the average posterior probabilities for most likely class membership ranged between 0.70 to 1.0, suggesting good clustering accuracy. Table 2.5 presents the test of the best clustering solutions (among solutions associated with two to eight clusters).

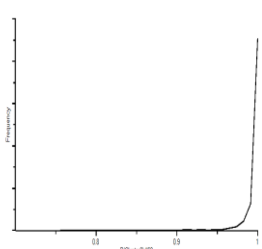
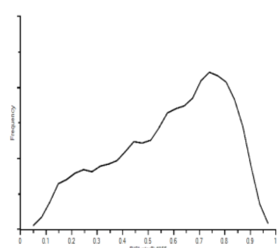
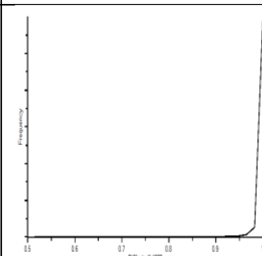
In addition to cluster membership, AMOS provides a probability of membership and probability distribution for each individual case, which helps in better interpretation of clustering results. Table 2.6 shows the clustering accuracy of three individual cases using BLCA. The actual ST ability scores of each student and the probability assigned to three classes (and posterior distribution graphs) by BLCA are consistent, which shows the precision and validity of BLCA clustering results.

Table 2.5 Clustering Analysis Using BLCA Method

Solution	CS	PPP	Converged
2-cluster [a]	1.0003	0.59	Yes
3-cluster	1.0207	0.69	No
4-cluster	1.0236	0.82	No
5-cluster	1.0232	0.73	No
6-cluster	1.0214	0.83	No
7-cluster	1.0210	0.81	No
8-cluster	1.0234	0.66	No

[a]The best solution.

Table 2.6 The Clustering Accuracy of Three Individual Cases Using BLCA.

<table>
<tr><td></td><td></td><td>Case #1 a student correctly classified as a holistic thinker with a probability of 1.00</td><td>Case #2 a student correctly classified as a holistic thinker with a probability of 0.71</td><td>Case #3 a student classified as a holistic thinker with a probability of 0.81</td></tr>
<tr><td rowspan="7">The actual seven ST Ability Score of each case</td><td>Interaction</td><td>100.0</td><td>66.7</td><td>0.0</td></tr>
<tr><td>Autonomy</td><td>80.0</td><td>40.0</td><td>20</td></tr>
<tr><td>Change</td><td>50.0</td><td>66.6</td><td>33.3</td></tr>
<tr><td>Uncertainty</td><td>83.3</td><td>80.0</td><td>0.0</td></tr>
<tr><td>Complexity</td><td>83.3</td><td>33.3</td><td>16.7</td></tr>
<tr><td>Hierarchical View</td><td>60.0</td><td>60.0</td><td>0.0</td></tr>
<tr><td>Flexibility</td><td>100.0</td><td>80.0</td><td>0.0</td></tr>
<tr><td colspan="5">Clustering result for three case studies</td></tr>
<tr><td rowspan="2">Probability of clustering of each sample in each class</td><td>Probability (holistic)</td><td>0.99</td><td>0.71</td><td>0.01</td></tr>
<tr><td>Probability (reductionist)</td><td>0.01</td><td>0.29</td><td>0.99</td></tr>
<tr><td colspan="2">The posterior probability distribution for the class with the highest chance (the bold number above)</td><td></td><td></td><td></td></tr>
<tr><td colspan="2">Interpretation of each case’s prediction</td><td>Very accurate prediction, which means this student strongly clustered as a reductionist student.</td><td>This student even has a higher chance to be clustered in the more holistic thinker cluster (see the frequency peak is after 0.71), which presents the prediction accuracy of the BLCA clustering.</td><td>This student has a high probability of being clustered as a more reductionist thinker, which shows a good predictive power of the BLCA clustering.</td></tr>
</table>

Based on the average of seven ST dimension scores of each cluster, we found out one cluster belongs to students with relatively higher ST scores. Consequently, this cluster is the more holistic cluster. On the other hand, the other cluster consisted of students with relatively lower ST dimensions scores, and it is called the more reductionist cluster. Based on the clustering result, 60.3 percent of the engineering students (n=196) belonged to a cluster that tended toward a more reductionist thinker (that is, a low OST cluster). These engineering students possess ST dimensions scores toward the reductionist spectrum of Table 2.2. Conversely, 39.7 percent of the engineering college students (n=129) belonged to a cluster that tended toward a more holistic thinker (see Table 2.2). Table 2.7 indicates the mean percentage of ST dimensions scores, as well as one standard deviation below and above the mean (corresponding to low and high levels, respectively) two identified engineering students' clusters using BLCA. Based on the clustering result, the average of engineering students in the more holistic cluster have some ST ability dimensions scores (almost in 40.0% to 60.0% range), and almost all of the students in the more reductionist cluster had low ST ability dimensions scores.

Table 2.7 The Mean, Low, and High Levels of ST Ability Scores of Engineering Students' Clusters by BLCA.

Cluster	Level	*Interaction*	*Autonomy*	*Change*	*Uncertainty*	*Complexity*	*Hierarchical View*	*Flexibility*
More holistic thinker students N=129 (39.7%)	High[1]	63.42	49.41	43.73	47.77	60.81	46.30	77.18
	Mean	59.73	46.07	41.60	45.37	58.06	43.70	73.63
	Low[2]	56.04	42.73	39.46	42.97	55.30	41.09	70.08
More reductionist thinker students N=196 (60.3%)	High[1]	36.76	38.37	40.35	30.30	39.91	34.11	56.41
	Mean	34.17	35.12	38.22	28.25	37.36	31.79	54.11
	Low[2]	30.48	31.78	36.09	25.85	34.60	29.18	51.81

[1]: one standard deviation above the mean; 2: one standard deviation below the mean.

2.5.2.2 Kmeans clustering

Kmeans clustering using SPSS software version 26.0 was performed to group the engineering students according to their ST dimensions scores. Kmeans in SPSS does not provide any test of the best clustering solution. As a result, we used the clustering Silhouette analysis (as an additional test) to validate and find the best clustering solution for Kmeans clustering. The clustering Silhouette result showed that the 2-cluster solution is the best solution for the data. Table 2.8 shows the result of the Silhouette analysis according to the comparison of Kmeans clustering results from 2-cluster to 8-cluster solutions. The 2-cluster solution has the highest mean value, among other solutions, indicating the 2-cluster solution by Kmeans is the best clustering solution among seven tested solutions for the dataset. The distances between the two cluster centers were 50.70. According to the ANOVA, the two identified clusters were significantly different from each other in six dimensions of ST ability; the Change dimension was the exception. This result is consistent with BLCA results, as shown in Figure 2.3, which shows that the Change dimension was the only ST dimension for which the boundaries of the two clustering methods intersect.

Table 2.8 The Silhouette Result for Kmeans Clustering.

Number of tested clusters	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Mean	0.188*	0.150	0.135	0.135	0.138	0.138	0.141
Std. Error of Mean	0.005	0.005	0.005	0.005	0.005	0.005	0.005

*The best solution

2.5.2.3 TwoStep cluster

We used the TwoStep clustering using SPSS software version 26.0 to group the engineering students based on their ST dimensions scores. The result showed that the 2-cluster solution achieved the lowest Schwarz's Bayesian Criterion (BIC) of 1732.3, which indicates the 2-cluster solution is the most appropriate solution, among others. This result is consistent with BLCA and Kmean results.

2.5.2.4 The comparison of three clustering methods

Table 5.9 below shows the means and standard deviations across the three clustering methods reported. As shown in Table 2.9, all three clustering methods categorized engineering students into two distinct groups, one more holistic systems thinkers and one more reductionist systems thinkers within consistent ST dimensions score ranges. The descriptive statistics across the three methods are reliable and consistent, which gives validity to the result of BLCA as the main clustering method. Looking into each dimension, we found that students in the holistic cluster scored higher in Interaction, Uncertainty, Complexity, Flexibility skill dimensions relative to students who were in the reductionist cluster. No pure holistic thinkers were found in the sample size. (e.g., 90% range) across three clustering methods. The score differences for Autonomy, Change, and Hierarchical View were relatively close for all three clustering methods.

Table 2.9 The Comparison of Three Clustering Analyses.

Clustering Technique		Statistics	*Interaction*	*Autonomy*	*Change*	*Uncertainty*	*Complexity*	*Hierarchic*	*Flexibility*
BLCA	Toward holistic cluster n=129	*M*	**59.7**	**46.0**	**41.6**	**45.3**	**58.0**	**43.7**	**73.6**
		SD	3.6	3.3	2.1	2.4	2.7	2.6	3.5
	More reductionist cluster n=196	*M*	**34.1**	**35.1**	**38.2**	**28.2**	**37.3**	**31.7**	**54.1**
		SD	2.5	3.2	2.1	2.0	2.5	2.3	2.3
K-means	More holistic cluster n=126	*M*	**64.2**	**51.9**	**38.6**	**46.2**	**60.5**	**43.4**	**74.7**
		SD	6.3	7.5	4.6	6.1	6.9	7.3	7.1
	More reductionist cluster n=199	*M*	**33.9**	**32.7**	**40.7**	**29.4**	**38.0**	**33.1**	**55.2**
		SD	5.9	6.7	5.8	6.4	6.9	6.1	7.6
TwoStep	More holistic cluster n=136	*M*	**61.7**	**42.9**	**36.8**	**48.5**	**60.5**	**44.8**	**78.5**
		SD	6.6	8.2	4.9	6.1	6.7	7.1	5.9
	More reductionist cluster n=189	*M*	**34.1**	**38.2**	**42.0**	**26.9**	**36.8**	**31.6**	**51.5**
		SD	6.2	7.2	5.6	5. 7	6.8	6.0	7.3

[1]Reductionist cluster; [2]Holistic cluster

About 89.8 percent of cases (292 out of 325 cases) clustered identically by both the BLCA and the Kmean method clustering methods. Additionally, 93.2 percent of cases (303 out of 325 cases) clustered identically by both the BLCA and TwoStep clustering methods, with 83.4 percent of cases (271 out of 325 cases) clustered identically by both the Kmean and TwoStep clustering methods. The detailed cross-tabulation results of three clustering methods are presented in Table 2.10 and show good consistency and accuracy across clustering methods.

Table 2.10 Cross-tabulation among the Results of Three Clustering Methods

Cross-tabulation between BLCA and Kmean clustering					
			BLCA clustering		Total
			1	2	
Kmean clustering	Reductionist cluster[1]	% within BLCA clustering	**91.8%**	14.7%	61.2%
	Holistic cluster[2]	% within BLCA clustering	8.2%	**85.3%**	38.8%
Cross-tabulation between BLCA and TwoStep clustering					
			BLCA clustering		Total
			1	2	
TwoStep clustering	Reductionist cluster[1]	% within BLCA clustering	**91.8%**	7.0%	58.2%
	Holistic cluster[2]	% within BLCA clustering	8.2%	**93.0%**	41.8%
Cross-tabulation between TwoStep and Kmean clustering					
			TwosStep clustering		Total
			1	2	
Kmean clustering	Reductionist cluster[1]	% within TwoStep clustering	**89.4%**	22.1%	61.2%
	Holistic cluster[2]	% within TwoStep clustering	10.6%	**77.9%**	38.8%

2.5.3 ST Score by Student Cluster

Although the findings of this study show that engineering students tend to be more toward the systems-thinker cluster (that is, more holistic systems thinking), students in this cluster, as shown in Figure 2.3, still possess ST ability scores below 60.0% (except Flexibility dimension). In addition, the majority of engineering students scored between 33.0 to 55.0 (Figure 2.1). The mean and median of the total aggregate ST scores of engineering students indicate that the average of students scored is lower than 50%, and also half of the sample scored less than 43.60 toward reductionist. In other words, the study shows that no pure holistic group of students was identified. This result emphasizes the need to develop effective educational practices to improve students' level of ST ability in order to better equip them for careers in the complex organizations of the future. Such practices could include revising existing curricula, offering special professional development courses, providing faculty training in teaching ST, and organizing outreach activities and workshops.

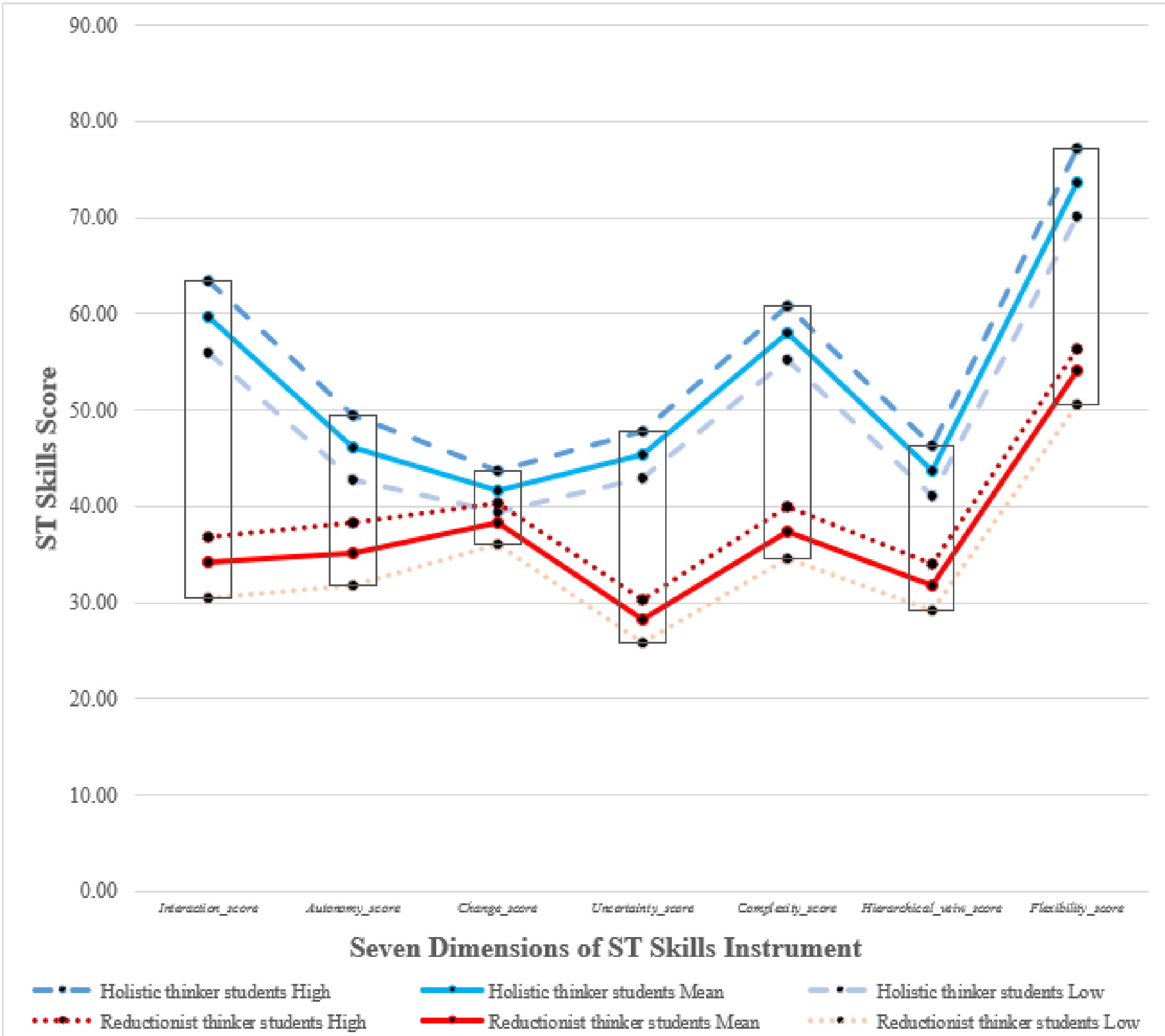


Figure 2.3 Clustering of Engineering Students (n=325) Using BLCA based on Their ST Ability in Three Levels.

2.5.4 ST Score by Academic Major

To better understand the impact of ST ability on engineering students, we categorize engineering students by major of study. According to the operational definition of the STQ instrument (Table 5.2) and the level of ST ability of engineering students with different majors of study, we inferred the following interpretation. Regarding the Level of Interaction skill, Software and Industrial engineering students have a relatively higher average level of interconnectedness in coordination and communication among multiple systems than other engineering students, and computer science students have a relatively lower average level of Interaction skill than others. Regarding Autonomy skill, Software, Biomedical, Biological engineering students have a relatively higher average level of balance between local-level autonomy versus system integration than other engineering students, and Petroleum engineering students have a relatively lower average level of Autonomy skill than others. Aerospace engineering students found to be a relatively higher average level of Change skill than other students, and Petroleum engineering students have a relatively lower average level of Change skill than others. Industrial engineering students have a relatively higher average level of Uncertainty and Complexity than others. Petroleum engineering students have a relatively lower average level of Uncertainty, Hierarchical View, and Flexibility ability than other engineering students. Software engineering students have a relatively higher average level of Hierarchical View (e.g., understanding system behavior at the whole versus part level) and Flexibility (accommodation of change or modifications in systems or approach) ability than other engineering students.

The potential mean differences of Total Aggregate ST score of students across major of engineering study across the two identified clusters—more holistic vs. more reductionist are depicted in Figure 2.4 and discussed below. The independent-samples t-test is performed to investigate the significant difference between more holistic vs. more reductionist for each major of engineering study. Two clusters of Aerospace engineering students (more holistic vs. more reductionist) are significantly different from each other according to $t(df=26)=-6.36$ and p-value<.001. Similarly, two identified clusters in each major of engineering study are significantly different from each other, except for the Petroleum engineering category. Since the two clusters of more holistic vs. more reductionist are significantly different in 11 out 12 major of engineering studies, we can further interpret these differences between two clusters as follow: All students in different major of engineering studies (except for Petroleum engineering) in the more holistic cluster have a significantly higher average level of Total Aggregate ST than more reductionist cluster. This further validates the main clustering result of the study. In the more holistic cluster (red line in Figure 2.4), the average Total Aggregate ST score (considering all seven ST dimensions) of Biological and Electrical Engineering students is relatively higher than other engineering students, and Petroleum engineering students have relatively lower total score than others. In the more reductionist cluster (blue line in Figure 2.4), Industrial and Computer engineering students have a relatively higher level of Total Aggregate ST score than engineering students, and Petroleum engineering students have a relatively lower total score than others. For further comparison between majors of engineering studies, see Figure 2.4.

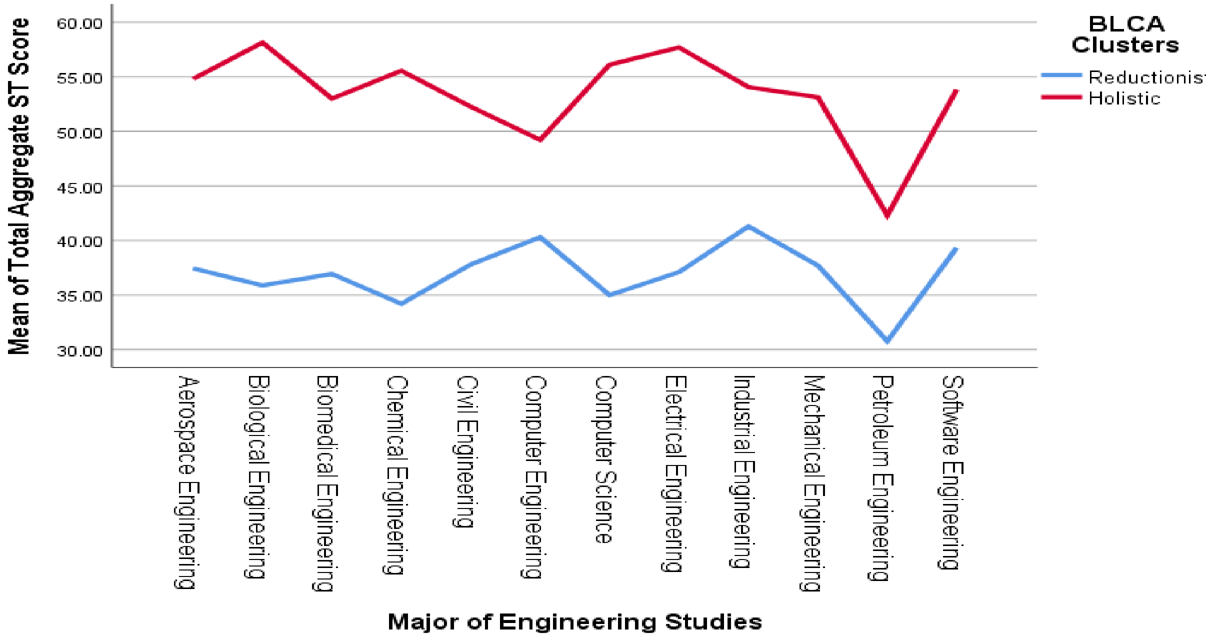


Figure 2.4 The Mean of Total Aggregate ST Score of two Clusters of Engineering Students across Major of Study

2.6 Discussion and Further Analyses

2.6.1 ST ability of engineering students

Based on the 2-cluster solution, engineering students were grouped into two groups, one of which was more holistic thinkers and the other of which was more reductionist thinkers. Table 2.11 summarizes the potential ST capabilities/skills of engineering students in the more holistic cluster versus the more reductionist cluster. These potential capabilities/skills are derived from the operational definition and application of the STQ instrument based on the average systems thinking scores of each of the two identified clusters among engineering students. For instance, engineering students who tended to be more holistic thinkers in more holistic cluster scored relatively higher than engineering students in the more reductionist cluster in the first dimension of STQ instrument (that is, level of interaction: Isolation (N) vs. Interconnectivity (I)), see Figure

2.3. Then, the score differences between two clusters of engineering students were interpreted based on the operational definitions of the STQ instrument by the developer of the instrument showing some potential systems thinking capabilities of engineering students. Engineering students in the more holistic cluster might prefer working in a collaborative, global environment, while their counterparts prefer working in a private, local environment. Moreover, engineering students in the more holistic cluster might have excellent communication ability and easily adaptable to any new interaction, while their counterparts tend more stable and local interaction. The main potential capabilities for other dimensions extracted, as explained above. Figure 2.3 below depicts the difference between the two clusters in regard to the seven ST ability dimensions in three levels of high, mean, and low in each cluster.

Table 2.11 Main Potential Capabilities of Each Engineering Student Cluster.

Pair of Dimensions	Dimension Description	Engineering Students in more Holistic Thinker Cluster	Engineering Students in more Reductionist Thinker Cluster
Level of Autonomy *Autonomy (A)* vs. *Integration (G)*	Denotes the inclination/comfort zone of an individual to manage the integration of multiple systems.	❖ More comfortable with making collaborative decisions ❖ Emphasize more on global performance, but still focus on local performance. ❖ Examine different elements of the issue as a whole, but still focus on some details of the issue as well.	❖ Prefer to take independent decisions. ❖ Emphasize more on the local performance. ❖ Examine different elements of the issue in detail.
Level of Interaction *Isolation (N)* vs. *Interconnectivity (I)*	Signifies the inclination/comfort zone of an individual to handle the incorporation of multiple systems.	❖ Prefer working in a collaborative, global environment. ❖ Prefer general work plans, and can work with flexible plans, if needed. ❖ Have excellent communication ability and easily adaptable to any new interaction.	❖ Prefer working in a private, local environment. ❖ Prefer detailed pre-defined work plans. ❖ Prefer local and stable interactions.
Level of Change *Embracement of Requirements (Y)* vs. *Resistance to Requirements (V)*	Deals with individuals' propensity to accept the change in complex phenomena.	❖ Predilection to work in more static and controllable work environments. ❖ Reluctant to make any alternation in the complex system. ❖ Unwilling to incorporate new ideas and technology associated with the systems.	❖ Analogous to engineering students in the more holistic cluster.
Level of Uncertainty *Stability (T)* vs. *Emergence (E)*	Signifies individuals' predisposition in making decisions under the stochastic nature of the system.	❖ Are more comfortable with working in a turbulent environment but still inclined toward the static environment. ❖ More apt in handling unexpected change due to external perturbation, but still would rather work in manageable work environments.	❖ Not prefer to work in an environment where change is continuous. ❖ Predilection to work in more manageable work environments.
Level of Complexity *Complexity (C)* vs. *Simplicity (S)*	Describes the individual's comfort level to work in complex system domains.	❖ Shows dexterity in handling large complex systems problems. ❖ Have strong critical reasoning capability to delve deeply into problems and complex phenomena.	❖ Lean toward dealing with less complex phenomena. ❖ Have predilection for avoiding working in an intricate multiple systems environment.

Table 2.11 (Continued)

Pair of Dimensions	Dimension Description	Engineering Students in more Holistic Thinker Cluster	Engineering Students in more Reductionist Thinker Cluster
Level of Hierarchical View *Reductionism (R)* vs. *Holism (H)*	Describes individuals' understanding level of systems nature holistically versus fractionally.	❖ Has a better understanding of the bigger picture of complex problems. ❖ Think in a more holistic way than a reductionist student, but still trap in underemphasize of details. ❖ Prefer a working solution, but still over-analysing the problems.	❖ Has difficulty to understand the bigger picture when given intricate details of a system ❖ Think in a reductionist way and under-emphasis of details. ❖ Analyse different technical aspects of a problem to find the best optimal solution.
Level of Flexibility *Rigidity (D)* vs. *Flexibility (F)*	Entails an individual's preference for altering plans.	❖ Enthusiastic about incorporating innovative or path-breaking ideas to find the solution. ❖ Can think beyond traditional ways to solve a problem ❖ Willingness and aptitude to respond to fluctuating circumstances.	❖ Enthusiastic about incorporating innovative or path-breaking ideas to find the solution, some degree less than holistic students. ❖ Can think beyond traditional ways to solve a problem but still has some limitations. ❖ Willingness and aptitude to respond to fluctuating circumstances, at some level less than holistic students.

The study findings are consistent with other studies that have demonstrated that students—especially engineering students—need to be trained in a way that helps them work in a more dynamic and changing business environment (Assaraf and Orion, 2005; Frank, 2000; 2002; Sweeny and Sterman, 2000). To engage more effectively in complex system problems, more holistic thinkers are needed (NSF, 2017; NSF, 2020); however, both identified clusters lack students with pure holistic features. The NSF stresses the need for advancing holistic engineering formation in the global market. Additionally, there is a workforce systems skills/capability gap identified in the literature, which share the same concern as current study findings (Dagli and Kilicay-Ergin, 2008; Trochim et al., 2006; Jaradat et al. 2019).

2.7 Conclusion

This study assessed the current ST ability of college engineering students. The study 1) provided an ST profile for each engineering student based on the seven ST dimensions, 2) produced a total aggregate of ST score for each engineering student and showed its frequency among the population of students, 3) grouped and clustered engineering students according to their seven ST skill scores to better manifest the individual ST differences among them, and 4) compared the differences between ST ability of students across 12 major of engineering studies to better present the differences between engineering students. The main result of the study shows that a 2-cluster solution is the best fit to group the engineering students among the population of interest. Based on the 2-cluster solution, engineering students are grouped into more *holistic thinkers* and more *reductionist thinkers*.

Below is a summary list of potential implications of the study in terms of education, practice, and policy:

- Revisit the engineering education curriculum to include more systemic syllabus, workshop, and laboratory courses to introduce systems theory concepts, system dynamic science, and systemic approaches in complex systems domain (Frank, 2000, 2002; Sweeny and Sterman, 2000).
- Since any major change in engineering students' formation can start from earlier stages, more emphasis should be driven toward the K-12 education curriculum and

introduction of systemic thinking basic concepts (Assaraf and Orion, 2005; Ossimitz, 2000).

- The identification of the ST skills/capabilities of engineering students provide direct utility to focus more on the specific ability that engineering students lack. This would reduce the burden of long training costs for employers.
- Literature indicates that socio-technical and complex system problems need more systemic thinkers since these problems contain different components, including technical, culture, policy, and social (Boardman and Sauser, 2006; Churchman, 1979; Jaradat et al. 2017; Mitroff, 1998). Handling socio-technical systems require a cadre of individuals who can take a more holistic approach. These holistic approaches can be categorized as big picture analysis—holistic mental mapping of complex system problems, understanding the interactions of a robust casual chain of events—understanding complicated interrelationship and interactions of different components of complex system problems beyond the simple one-cause one-effect approach, integration perspective within complex systems—consideration of requirement of the whole instead of only focusing on local requirements, and chaos management— flexible and resilient plans to adapt to the emergent and unintended problems of complex systems.

The current study is the first task out of three tasks planned for a big study supported by the National Science Foundation (NSF). The survey data set from task 1 will be used as input data for building the predictive model in order to investigate the impact of various factors on the level of ST ability of engineering students. In the model, the total aggregate ST score will be used as the response variable, whereas four types of factors, including cognitive, demographic, academic, and institutional, will serve as input variables. The list of factors was developed based on extant literature and established theoretical framework (deductive and inductive reasoning) in the field of cognitive phycology and engineering student success. The values for each factor and response will be extracted from the task 1 data set. Cognitive factors will be assessed using the measures described below. For the demographic, academic, and institutional factors, participants will respond to a series of multiple-choice and Likert rating scale items at the end of the STQ instrument, including different questions relevant to general demographic, academic, and institutional factors.

Cognitive factors in the model are complex problem-solving ability factors and will include measures of deductive reasoning ability and inductive reasoning ability. Problems from the MCAT have traditionally served as measures of deductive reasoning because these math problems are well-defined; if acquired rules are applied correctly, the solution is assured. Inductive reasoning tasks will include three ill-defined problems: a) Raven’s Figural Analyses, b) Remote Associates Test (RAT), and c) Series Completion Task. WMC has been shown to mediated complex problem-solving ability (Wiley and Jarosz, 2012) and will be measured to determine the degree to which it also mediates the relationship between complex problem-solving ability and ST capability. Future studies could delve into how other psychological factors, such as personality traits, self-efficacy, etc., might influence the level of engineering students’ systemic thinking ability. These factors can be considered in future studies, as well.

Finally, task 3 of this project will identify gaps between current engineering students’ systems thinking capability and employers’ systems thinking needs. This method, called the ST-cap method, tries to find and address the systems thinking gap between engineering students and potential employers. To evaluate the ST needs of employers, we will utilize the STQ-Environment instrument. This survey examines the degree of complexity in the system and environment that must be engaged by practitioners. The work of the unit in focus for the effort must take place within an environment. Establishing the nature of this environment against the students' ST ability is the focus of the STQ instrument. Upon completion, the complex nature of the environment of the unit is captured in relation to the abilities (Table 5.2). The STQ-Environment instrument examines the degree of perceived complexity that exists in the environment of a focal system/organization. This was captured by an assessment of the seven dimensions of ST (Table 5.2) in relation to the environment through a 46-question web-based survey instrument. Each question on the STQ-Environment is a binary forced-choice item in which participants choose their most-preferred response. The scoring for the STQ-Environment follows the same calculations used for the ST ability analysis to facilitate the comparison of the two.

Bigger sample sizes from different universities in different regions will shed more light on research findings and give the opportunity to compare the results across different universities and geographic locations. Clustering methods used in this study categorize data into clusters based on the distance between data-points, and consequently, these methods do not give the exact measure of how holistic (or how reductionist) each engineering student is.

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CHAPTER III

DEVELOPMENT OF PERCEIVED COMPLEX PROBLEM-SOLVING INSTRUMENT IN DOMAIN OF COMPLEX SYSTEMS

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3.1 Abstract

The ability to solve modern complex systems becomes a necessity of the 21st century. The purpose of this study is the development of an instrument that measures an individual's perception toward solving complex problems. Based on literature and definitions, an instrument with four stages named Perceived Complex Problem-Solving (PCPS) was designed through exploratory and confirmatory stages. The instrument is validated and scaled through different models, and the final model is discussed. After completing validation and scale development of the PCPS instrument, the final model of the PCPS instrument was introduced to resolve the gap in the literature. The final model of the PCPS instrument is able to find and quantify the degree of perception an individual holds in dealing with complex problems and can be utilized in different settings and environments. Further research about the relationship between Systems Thinking and CPS revealed individuals with a high level of systems thinking have a better understanding of the characteristics of complex problems and so better perception of CPS.

Keywords: complex problem-solving, systems thinking, systems thinking skills/preferences, perceived complex problem-solving instrument, complex systems, exploratory and confirmatory factor analysis, scale development, SEM.

3.2 Introduction

Modern complex systems deal with more socio-technical dimensions and interact directly with the surrounding environment, and this interaction creates challenges and issues (Jaradat, 2015). The management of this turbulent work environment mandates the need for a skillset that involves creativity, continuous learning, innovation, and collaboration. Complex problem-solving skills become a necessary competence in today's workforce (Mainzer, 2009) and attract job seekers. This is evident through different programs that emphasize finding better approaches and methods in solving complex-system problem domains, For example, in different programs such as The Program for International Student Assessment (PISA), The Program for the International Assessment of Adult Competencies (PIAAC), and the O*net job database (the U.S. Department of Labor's Occupational Information Network) (Hubbard et al., 2000). PISA is an assessment of the Organization for Economic Co-operation and Development (OECD), which includes the assessment of students' problem-solving skills and direct assessment of life competencies that apply across different areas of the school curriculum. PIAAC is an international assessment of adult skills managed by the OECD, which is currently being implemented by 25 countries in Europe, the Americas, and Asia. Although complex problem-solving has received attention in the literature and from scholars, still not clearly defined, and the continued divergence in the definitions and perspectives will muddle the field and slow the progress of developing methods that can be applied to different disciplines. (Kyllonen, Anguiano Carrasco, & Kell, 2017).

Within the 21st century, modern complex systems still confront challenges with a high level of *integration*, *ambiguity, uncertainty,* and *interdependence* between systems and their related elements, making blurred the lines between technical, social, political, managerial, and organizational considerations (Boardman & Sauser, 2006; Jaradat, Keating, & Bradley, 2017). Ackoff (1995) claimed that one of the approaches that help us to evaluate and understand the complexities and challenges of third-millennium organizations is a systemic approach or systemic attitude, and he stated, in dealing with complex systems problems, one should focus on the system as a whole, rather than on the parts (Ackoff, 1995). In system theory, problems are studied based on their conditions, requirements, and developments, as well as their contributing factors and their interrelationships, are examined, and appropriate solutions are provided. Therefore, systems thinking is necessary for a more comprehensive and systematic approach in dealing effectively with modern complex systems and their problems/challenges. The study of factors that strengthen complex problem-solving skills helps employers hire competent employees and invest in their training.

In the 2000s, there was a belief that systems thinking can be an answer to complex systems problems (Jackson, 2001; Keating, Kauffmann, & Dryer, 2001; Maani & Maharaj, 2002), and there is convergence around their definitions (Funke, 2012; Stadler, Becker, Gödker, Leutner, & Greiff, 2015), This belief was translated later into action where some studies appeared to show the significance of systems thinking in the domain of complex systems and recruiting employees (Karam et al., 2020; Nagahi et al. 2020, Nagahi et al., 2021). however, what remained unanswered is the relationship between an individual's system thinking and his/her general perception of different stages in the Complex problem-solving process---that is a current gap in the literature.

To address the gap and to improve the body of knowledge, the aims of the study are 1) to develop and validate a new perceived complex problem-solving instrument and to 2) investigate the relationship between systems thinking and complex problem-solving using the developed instrument. The intent of the study is also to compare the effect of seven different dimensions of systems thinking, discussed later (Jaradat, 2015), on the performance of complex problem-solving.

The contribution of the study has two dimensions. From a methodological dimension, because of the simulation method in this field and the lack of an instrument that is easy to use in general and being base on CPS theories, this study develops and validates a new complex problem-solving instrument in the literature. Several validity and reliability measures are conducted to establish the development of the instrument. From a theoretical dimension, this study is important for academics since it helps to bridge the literature gap in the field by providing comparisons and relationships between different systems thinking dimensions with the perception of complex problem-solving stages. From a practical dimension, this study emphasizes on the importance of employees who obtain high-level systems thinking and complex problem-solving skills to deal with modern complex system problems, so this study encourages HRM professionals to consider system thinking and CPS skills as work requirements in recruiting employees and hold training programs for both experienced managers and newcomers in the organization. This study can also be implemented in educational programs for students to evaluate and screen their skillset and capability in modern complex system problems.

An overview of complex problem-solving and systems thinking is provided next, followed by the research hypotheses, the research methods, and the analyses performed to assess the validity and reliability of the theoretical model. The study concludes with a discussion, implications, limitations, and future research.

3.3 Background and Hypotheses

3.3.1 Complex Problem-Solving

Modern complex problems are considered ill-defined problems with a lack of clear paths to obtain an optimal solution (Sternberg & Sternberg, 2016). With the growth of complexity, it is difficult for problem solvers to evaluate the performance of the system since extracting information might be difficult to achieve. So the problem solver have interactions with the task until he/she gets information about progression (Joachim Funke & Frensch, 1995) and reduce the gap between the initial state and the goal state by performing non-routine cognitive activities (Funke, 2012; Mayer & Wittrock, 2006).

The research area in problem-solving has begun in cognitive psychology with the experimental work of the Gestaltists in Germany (e.g., Dunker, 1935 in Funke & Frensch, 1995) typically with simple laboratory work (e.g., the "disk problem" later known as the "Tower of Hanoi" (e.g. Mayer, 1992) and Dunker's " X-ray" problem (Ewert & Lambert, 1932) and It was thought it could be generalizable to more complex problems (Funke & Frensch, 1995). At the beginning of the 1970s, researchers gradually became convinced that the theoretical concepts and empirical findings from simple laboratory tasks could not be generalized to complex real-world problems, and even under different circumstances, the basic complex problem-solving processes were different (Sternberg, 1995). Since 1975, after global events such as the oil crisis, a new path has opened in the psychology of thinking that addresses complex problems and led to different reactions in North America and Europe (Funke & Frensch, 1995). The two ideas formed do not define problem-solving in the same way, and their divergent definitions led to different measurements of complex problem-solving.

A) Two major approaches emerged in Europe, in Britain by Donald Broadbent (Broadbent, 1977) and in Germany, by Dietrich Dörner (Dörner, 1975) in (Dörner & Wearing, 1995)). Both approaches focused on complex laboratory tasks based on computer simulation, but these approaches differed somewhat in theoretical objectives and methods. In the British approach, mathematical problems were used in computer simulation systems to examine cognitive problem-solving processes under the consciousness and unconscious.

In German school, (Funke & Frensch, 1995) stated that one obstacle must be removed in simple problem-solving, while in complex problem-solving several obstacles require a set of cognitions and prioritization programs to move forward the target situation (Funke & Frensch, 1995). (Dörner & Funke, 2017) claimed Funke and Frensch's definitions did not fully include the content or the relationship between the simulation and the real world. Therefore, they redefined a practical CPS as a collection of self-regulated psychological process and activities which combine cognitive motivational and emotional aspects in a dynamic environment to achieve a bricolage and not perfect or optimal solutions. Complex problems require high knowledge and collaboration among many people (Dörner & Funke, 2017). In PISA 2012, the definition of complex problem-solving is the individual's capacity for cognitive processing to understand and solve problem situations (OECD, 2014). The PISA 2015 defines collaborative problem-solving, and it showed that the students with a high level of collaborative problem-solving abilities could successfully carry out complicated problem-solving tasks with high collaboration complexity (OECD, 2016). In PIAAC, it defines problem-solving in technology-rich environments (OECD, 2012b).

Base on German school definition, In the early 1980s, Dörner introduced the computer simulation scenario of "microworlds" such as Tailorshop (Dörner, 1980), "Lohhausen" (Dörner, Kreuzig, Reither, & Stäudel, 1983) with several variables, to allow experimental research of complex problems under controlled conditions (Brehmer & Dörner, 1993). Researchers in this field have found that although the upper limit of complexity is not limited, the lower limits can be identifiable (Greiff & Funke, 2009). So they introduced "minimal complex systems" scenarios consist of a single task or problem(J. Funke, 2014). Then "multiple complex systems" approach (Greiff et al., 2015) was introduced in response to the weaknesses of minimal complex systems.

(B) The CPS definition in the North American approach emphasizes "the study of cognition in complex real-world conditions" (Funke, 2010)p.135) and several techniques and tools developed in this approach. The O*net staff survey, which is the result of the efforts of the US Department of Labor, has developed several tools for measuring skills, knowledge, and abilities. It has assessed the importance of complex problems-solving in different occupations by eight items in the prototype version then revised them in one item (Hubbard et al., 2000; Peterson et al., 1995). Although other tools such as personal problem-solving (Heppner & Krauskopf, 1987), managerial problem-solving (Church et al., 1989), problem-solving styles (Cassidy & Long, 1996), social problem-solving (D'Zurilla & Maydeu-Olivares, 1995) developed in this approach, still research for the development of a general theory in the evaluation of complex problem-solving abilities are not presented in the North American literature.

Despite much research in this area, the difference between the concept of a "simple problem" and a "complex problem" is still somewhat obscure, but we know that the greater the number of variables and the greater the relationships between them, cause the more complexity of the problem (Funke, 2010; Joachim Funke et al., 2017). It is still an open question which measurement can best assess the complex problem-solving or whether various other constructions should be proposed (Kyllonen, Anguiano Carrasco, & Kell, 2017). After an extensive survey in the literature, And the lack of a suitable questionnaire to assess recognition of CPS and its process is still a current gap. Based on Stenberg's definitions in his book "Cognitive psychology" (Sternberg & Sternberg, 2016), of complex, insightful, and ill-structured problems and the processes of solving such problems, and also, the definitions and problem-solving processes in the prototype version of O*net questionnaire and its revision (Peterson et al., 1995) (Hubbard et al., 2000), we designed an instrument to assess individual's perception of complex problem-solving. The perceived problem-solving inventory does not directly assess problem-solving ability nor assessing one's function in a hypothetical problem situation. As stated in various sources in Heppner and Patersen (1982), individuals act in hypothetical situations different from real situations. This inventory evaluates a general knowledge of a person about complex problems and the process of solving them. True perception of complex problem-solving support us in distinguishing it from simple problem-solving. Know that as barriers between a given state and a goal state are complex, change dynamically during problem-solving, and intransparent. Different aspects of a given state and the goal state are obscure for problem solvers and hard to identify. Solutions are not immediately obvious and are a combination of activities as a result of interaction between different solvers and their situation and are not necessarily perfect or optimal. Awareness of these facts helps us to perform better and more realistically in passing the stages of real-world complex problem-solving.

In research conducted annually by The National Association of Colleges and Employers, problem-solving ability is one of the most important skills which employers seek on candidates' resumes. For example, the results of this annual survey showed that in 2016, employers, after the ability of the work team, are looking for problem-solving skills in work applicants (NACE, 2016). This skill topped the list in 2017 (NACE, 2017), and in 2020 (NACE, 2020), respondents, with 91.2%, stated that it was the first skill they were looking for in a candidate's resume. Also (Mourshed, Farrell, & Barton, 2013), in their survey, stated that employers are looking for students with high problem-solving skills in the entry stage. In another research (Casner-Lotto & Barrington, 2006), it was shown that problem-solving skills lead to job success in new workforce entrants. In annual O*net surveys, the results show that Problem Sensitivity was among the top 10 job needs among the various occupations, and the most need for complex problem-solving is in occupations with the highest demands, financial values , and high rewards, such as senior executives, lawyers, judges, crisis management managers, surgeons (Hubbard et al., 2000).

3.3.2 Systems Thinking

Numerous studies have linked complex systems and issues to systems thinking (e.g., Hossain, Nagahi, Jaradat, & Keating, 2020; Jaradat, 2015; Karam et al., 2020; Keating, 2008; Maani & Li, 2010; Sweeney & Sterman, 2000). Several researchers (Funke, 2012; Stadler, Becker, Gödker, Leutner, & Greiff, 2015) stated that the definitions of complex problem-solving and systems thinking have some overlap. (Funke, 2012) stated that five attributes distinguish complex problems from simple problems, which include 1) The complexity of the problem situation 2) The relationships between the variables involved 3) The dynamics of the situation and developments within the system, and the role of time 4) Partial or complete lack of transparency 5) Polytely (a Greek term for "many goals") and the possibility of conflict in the existence of several goals. (Dörner & Funke, 2017) considered at least three aspects for complex systems: 1) Different levels of abstraction, 2) Change (potentially unpredictable) over time, and 3) Knowledge-rich with many potential strategies. (Jaradat, 2015) introduced the characteristics of complex systems as 1) Increasing Complexity, 2) Ambiguity, 3) High Levels of Uncertainty, 4) Emergence, 5) Evolutionary Development, 6) Interconnectivity, and 7) Integration.

According to Checkland (1981), systems thinking is the thinking process by which the ability to think and speak in a holistic language to understand and deal with complex system problems. Flood and Carson (2013) and Richmond (2000) define system thinking as a framework that helps individuals to address complex things. Jaradat and his colleagues stated that an individual's systemic thinking capacity could be an effective response to a complex system problem(R. Jaradat, 2015; R. Jaradat et al., 2017). Although some tools and techniques have been developed for systems thinking such as(Frank, 2002; Hopper & Stave, 2008), Jaradat and his colleagues developed a system thinking skills/preferences instrument (with $\alpha = 0.91$) based on the grounded theory method, which is the first instrument for evaluating an individual's systemic thinking capacity, it includes seven dimensions: 1) level of complexity, 2) level of independence (autonomy), 3) level of interaction. 4) level of change, 5) level of uncertainty, 6) level of the systems worldview (hierarchical view), and 7) level of flexibility (see Figure 3.1)(Jaradat, 2015; Jaradat et al., 2017). This instrument was used in data collection for obtaining participants' predisposition for systems thinking skills.

Figure 3.1 Seven Dimensions of the "ST Skills Preferences Instrument" (Jaradat, 2015)

3.3.3 Hypotheses Development and the Proposed Theoretical Model

In research, systems thinking has been conceptualized in relation to dealing with complex systems and problems. But there are still gaps in this area.

A) Although Maani and Maharaj (2002) has attempted to show the relationship between systems thinking and performance in complex problem-solving in a sample of 10 participants, it has not yet been investigated the relationship between system thinking and the general perception of complex problems nontransparent aspects without specific training in complex problem-solving.

B) Most of the complex problems-solving research belong to German school and are based on computer simulation. In the North American approach, questionnaires were developed in the field of problem-solving importance (Hubbard et al., 2000), personal problem-solving (Heppner & Baker, 1997), problem-solving styles (Cassidy & Long, 1996), and social problem-solving (D'Zurilla & Maydeu-Olivares, 1995) regardless of novelty, simplicity or complexity of problems, and whether or not single or multiple barriers or goals. Therefore, there is a lack of a questionnaire that assess perceived complex problems-solving based on theories of complex systems and system science, and it should be easy to use for students, administrators, and employees.

In this study, to address these gaps, a questionnaire was developed to assess the individual's perceptions of complex problem-solving, inspired by the definitions in O*net (Hubbard et al., 2000) and "cognitive psychology" book (Sternberg & Sternberg, 2016) and Its validity and reliability evaluated by factor-analysis results. In addition to providing an examination of the relationship between systems thinking and perceived complex problem-solving, which enriches the body of current literature.

3.3.4 The Relationship Between Systems Thinking and Complex Problem-Solving

In many studies, systems thinking is considered an appropriate response to complexity because it provides a more holistic view of a problem area (Jaradat et al., 2017). Senge (1990) argued that due to overwhelming complexity, systems thinking is needed more than ever. Richmond (1993) described systems thinking as a superior approach in dealing with complexity. Sweeney and Sterman developed a list of systemic thinking features to assess students' capability in complexity (Sweeney & Sterman, 2000). In a study, Kinteng, Kaufman, and Dreyer examined whether systems thinking in an organization could provide a framework for analyzing and solving complex issues. The results of this study showed that systems thinking can prepare us to solve problems effectively in today's turbulent environment and can be used as a suitable framework for analyzing and solving problems in the management of organizations(Keating, Kauffmann, & Dryer, 2001). Jackson (2001), in his study on the effectiveness of the use of systems thinking in solving complex social problems, showed that systems thinking could be used as a coherent method to solve social problems. In another study in the Information and Communications Technologies sector, (Petkov, Petkova, Andrew, & Nepal, 2007) showed that techniques from soft systems and Multiple Criteria Decision Making (MCDM) could be effective in particular stages of a complex problem-solving intervention. Considering the widespread belief about the connection between systems thinking and complexity, Mani and Maharaj (2002) examined the relationship between systems thinking and performance in complex problem-solving for empirical substantiation of this belief (Maani & Maharaj, 2002). Based on simulation tests, they showed a certain type of systems thinking, and more importantly, the subject's approach to the problem is relevant to solving a problem.

Due to the five features of the complex problem (Funke, 2010, 2012) and the features of complex systems (Dörner & Funke, 2017; Jaradat, 2015; Jaradat et al., 2017) (as described in the previous section) and the systems thinking skills (Jaradat, 2015), it is evident that many of the complex problem-solving can be managed through systems thinking. System thinking skills help individuals understand the structure of problems, leading to better performance in problem-solving in complexity (Maani, 2002, p.7). However overall, what remains neglected in researches is effect of systems thinking on the general perception of complex problems and their nontransparent aspects. Therefore, in this study, this issue has been considered and different skills of systems thinking on complex problem-solving are evaluated.

3.4 Methodology

In this study, after validation of the Perceived Complex Problem-Solving (PCPS) instrument, the relationship between systems thinking and perceived complex problem-solving was examined. In other words, we investigated the impact of systems thinking skills preferences on the complex problem-solving perception of managers and students. To measure this relationship, two studies were performed. The first study targeted managers who face high levels of complex system problems in their organizations, and the second study targeted students as prospective future workforce. Two different samples were considered for testing the construct validity and internal consistency of the theoretical model across different samples. Figure 3.2 shows the research framework.

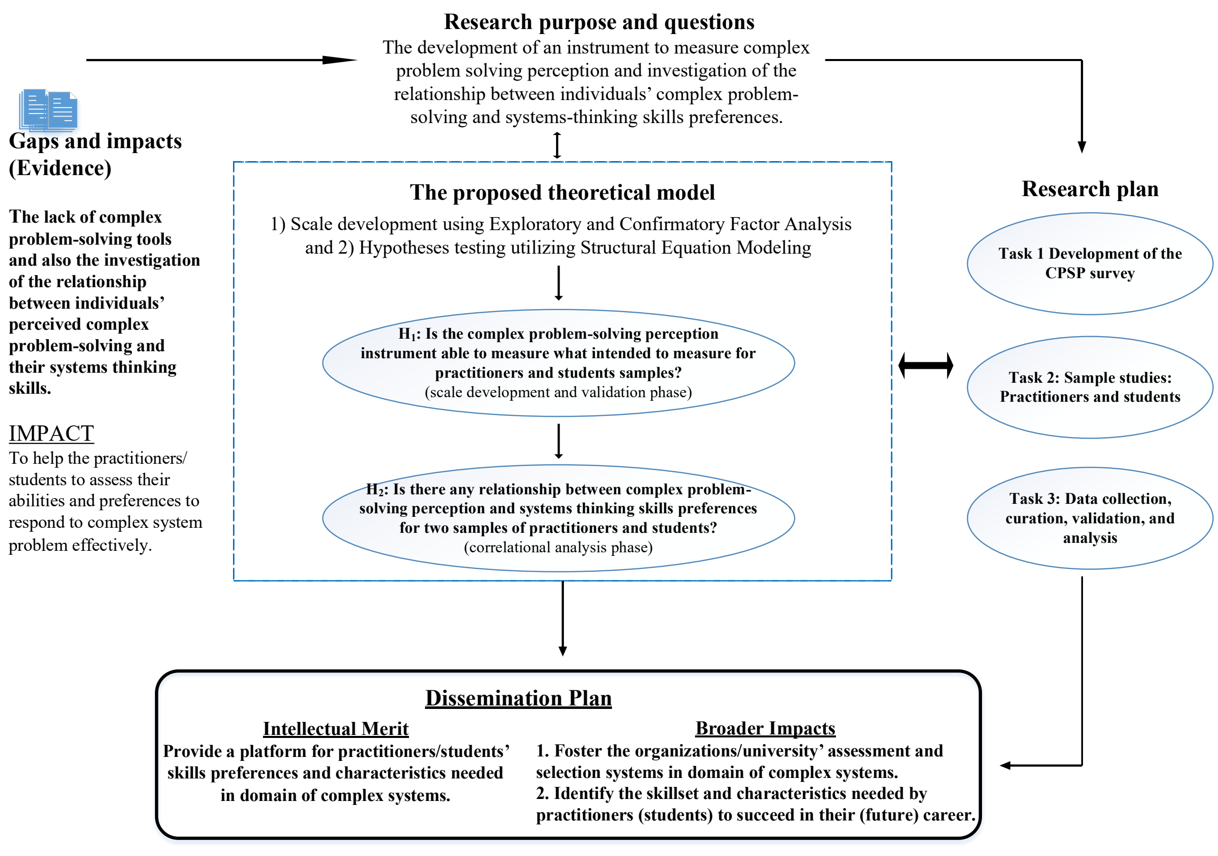

Figure 3.2 Second Research Framework

3.4.1 Materials

In this study, two questionnaires were used: The System Thinking Skills Questionnaire (with α = 0.92), developed by (Jaradat, 2015; Jaradat et al., 2017), with 39 questions, evaluates seven preferential categories/systems skills dimensions (Figure 3.1) and determines the individual's desire for Holistic or Reductionist thinking. Based on these dimensions, one score determines the total systems thinking score for each individual. Due to the lack of a suitable questionnaire to assess complex problem-solving abilities, a questionnaire consisting of nineteen five-Likert scale questions is developed and tested for validity and reliability (with 0.89). The questionnaire consists of four stages of complex problem-solving: 1) Problem Identification and Definition (questions 1-5; an example question in this dimension designed for students is "I am often facing unique and new problems in my engineering coursework."), 2) Information Gathering about problems and solutions (questions 6-11; an example question designed for students is "The methods, resources, or people through which information can be collected are not recognized well."), 3) Evaluating solutions and Developing Approaches (questions 12-16; an example question in this dimension designed for students is "It is hard to evaluate and assess the strengths and weaknesses of new ideas and solutions."), 4) Implementation Planning (questions 17-19; an example question in this dimension designed for students is "It is difficult to present and develop an executive plan for the realization of new ideas."), which totally assesses the ability of complex problem-solving. All items are scored on a five-point Likert scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree. A total score can be calculated as a general index of the perceived complex problem-solving of a person.

These questionnaires are used to measure individuals' assessment of their perception to solve complex problems and determine their systems thinking skills. Demographic factors are added to the proposed theoretical model.

3.4.2 Sample and Data Collection Procedure

3.4.2.1 Study 1

3.4.2.1.1 Participants

The statistical population of this study was Managers of the Governmental Executive Organizations in the South Khorasan Province in Iran. The respondents were n= 250, including 49 females and 201 males, and three CEOs, 46 deputies, 201 office managers. Respondents answered questions related to their age, managerial background, and work experience. The sample characteristics are shown in Table 3.1.

Table 3.1 Sample characteristics (Study 1).

Variable	Categories	Number (percentage)
Gender	Male	80.4%
	Female	19.6%
Age	≤ 30	1.6%
	31-40	36.4%
	41-50	50.0%
	51-60	10.8%
	60 ≤	1.2%
Level of education	High school diploma	0.0%
	Bachelor's degree	31.2%
	Master's degree	56.0%
	Ph.D.	12.8%
The major of study in the highest degree	Engineering	39.2%
	Social science	14.8%
	Business/Management	28.0%
	Health-related	2.0%
	Others	16.0%
Work experience (year)	Less than 10	8.8%
	11-20	48.4%
	21-30	36.4%
	More than 30	6.4%
Management experience (year)	Less than 10	58.8%
	11-20	33.6%
	21-30	6.4%
	More than 30	1.2%
Managerial level	CEO	1.2%
	Vice president/Deputy	18.4%
	Office manager	80.4%

3.4.2.1.2 Procedure

Step 1. The development of a complex problem-solving questionnaire

The initial version of the questionnaire was developed to assess an individual's perception of complex problem-solving. In order to determine its validity and reliability, according to (Lawshe, 1975), the initial version of the complex problem-solving questionnaire was given to 10 experts working in the field of public administration and management at different universities. The validity of its content (the relevance of the phrase, simplicity of the phrase, and the clarity of the phrase) was evaluated. Questions were accepted with CVI> 0.7, and then its reliability was evaluated among 250 employees with $\alpha = 0.895$. All "Cronbach's Alpha if Item Deleted" values were less than the overall Cronbach's Alpha of 0.895, suggesting all questions are reliable.

Step 2. The translation of the System Thinking Questionnaire

According to the literature (Solano-Flores, Backhoff, & Contreras-Niño, 2009; Van de Vijver & Hambleton, 1996), the systems thinking preference/skills were translated from their original form into the Persian language. The systems thinking skills instrument is translated to the Persian language through a panel of experts to accommodate better the language used by participants and to obtain a valid analysis. Then by comparing the two versions, modifications were made. The instrument was given to a small group of managers, and the reliability was evaluated with $\alpha = 0.841$, and the final survey was produced. All "Cronbach's Alpha if Item Deleted" values were less than the overall Cronbach's Alpha of 0.841, suggesting all questions are reliable.

The Persian version of the Complex Problem-Solving and Systems Thinking Questionnaires was used in this study. The sample size consisted of seventeen governmental executive organizations of South Khorasan. The selection criteria were based on Stratified

Random Sampling. Four hundred-fifty paper questionnaires were distributed among CEOs, deputies, and office managers of provincial organizations in the summer of 2020, and 250 questionnaires were returned.

3.4.2.2 Study 2

3.4.2.2.1 Participants

The statistical population of this study was students at Mississippi State University in the United States. Four hundred eighty-one students participated in the study. Of 481 collected responses, 373 students' responses were analyzed. The pair-wise deletion has been used in data analysis. The sample characteristics are shown in Table 3.2. The percentage of female and male respondents were 35.9% and 64.1%, respectively, and 67.3% undergraduate and 32.7% Graduate Studies. Their age range was from 18 to 60 with a mean of 28.7 years and SD of 10.0 years, and they were 83.9% of full-time students and 16.1% of part-time students. 9.9% distance learning students and 90.1 on campus. The mean CGPA of students was 3.45, with an SD of 0.54 ranging from 2.00 to 4.00. They have passed an average of 54.6 credits/hours in their program with an SD of 37.6.

Table 3.2 Sample Characteristics (Study 2).

Variable	Categories	Number (percentage)
Gender	Male	63.8%
	Female	36.2%
Ethnicity and Race	Asian	12.3%
	African-American	5.0%
	Caucasian	72.7%
	Hispanic	2.3%
	Middle Eastern	2.3%
	Multi-racial	3.1%
	Native American	1.2%
	Prefer not to disclose	1.2%
Currently employed (not including co-op/internship)	No	54.2%
	Yes	45.8%
Completed a co-op	No	83.1%
	Yes	16.9%
Completed a professional internship	No	78.1%
	Yes	21.9%

3.4.2.2.2 Procedure

A web-based survey was used to collect data for this study, and emails were sent to students in the Fall of 2020-2021. In this study, the original version of the Systems Thinking

Skills instrument (Jaradat, 2015) and the English version of the complex problem-solving instrument were used.

3.5 Data Analysis

3.5.1 Factor analysis and scale development

The purpose of this study is to bridge the literary gap with regards to an instrument for defining the Perceived Complex Problem-Solving (PCPS) of an individual. To meet this end, an individual's perception will be analyzed when faced with modern complex system problems. The scale development was conducted in two main stages—the exploratory and confirmatory stage. Other studies have applied similar development framework scales, initiated by studies with the pilot test (gathering experts' feedbacks), followed by a meticulous construction of the validity in EFA (exploratory stage). Finally, the framework is completed by constructing validity analysis using CFA (confirmatory stage)(Ambrose, Rai, & Ramaprasad, 2006; Jae-Nam & Young-Gul, 2005; Kishore, Swinarski, Jackson, & Rao, 2012; Schoenecker & Swanson, 2002).

Exploratory Factor Analysis (EFA) procedures were conducted as the dimension reduction (data-driven) technique using SPSS software, version 26; this shapes the initial theoretical model for the PCPS called the "baseline model" (Jaradat & Keating, 2016). The CFA, unlike EFA, is a theory-driven technique that requires a priori theoretical model (priori for this study was the baseline model resulted in EFA). Confirmatory factor analysis (CFA) procedures acted as the confirmatory stage utilizing AMOS, version 25, to confirm the structure of the baseline model. The CFA provided several analytics, including theory and hypothesis testing through construct validity, evaluation of method effects, examination of the stability of the factor model over participants, and a correlation between error terms.

3.5.1.1 Exploratory Stage

In the exploratory stage, factor analysis using SPSS software to determine the initial number of latent factors and respective items for each latent factor (construct) for the PCPS instrument. The following steps were conducted in the exploratory stage to achieve an initial theoretical model of the PCPS instrument.

3.5.1.1.1 Sample Size Adequacy

The data should be appropriate for the use of factor analysis(Rietveld & Hout, 2011). To assure sample size adequacy, three criteria have been tested including, the KMO test, Bartlett's test of Sphericity, and Anti-image correlation matrix. The adequate results have been achieved from KMO (study 1: $0.89 > 0.50$ and Study 2: $0.88 > 0.50$) and Bartlett test (study 1: Chi-square(136) = 1821.4, $p < 0.001$ and study 2: Chi-square(171) = 1876.1, $p < 0.001$)(Field, 2000; George & Mallery, 2003). In the Anti-image correlation matrix, high inter-correlations depict the importance of an item to a factor(Field, 2000). The matrix showed that almost all of the items loaded higher than 0.40 in respective factors, and there was no extreme multicollinearity between the items. These results prove that the data and sample size are appropriate for factor analysis (EFA framework).

3.5.1.1.2 Exploratory Factor Analysis Procedure

To perform EFA framework, a decision should be made in four criteria: 1) factor extraction method, 2) factor rotation method, 3) factor selection 4) choosing association matrix. Principal components analysis is the most frequently used EFA extraction method (Field, 2000) has been chosen as *the extraction method*. To interpret the meaning of the four retained factors, Orthogonal (Varimax) rotation has been chosen as the *factor rotation method*.

Factor Selection: To make the final decision about how many factors should be extracted, two criteria have been checked a) *Eigenvalues* shows variance explained by that particular factor out of the total variance(Field, 2000). Four factors have been kept with eigenvalues greater than one using Kaiser's criterion of retaining. b) The aim of the Scree Plot is to determine the optimal extracted factors. All the factors on the steep slope should be retained, and the other factors should be neglected (Field, 2000). Using the Scree Plot, four factors retained with eigenvalues greater than one.

These four factors extracted in EFA measure the four stages of the PCPS instrument, including Level of Problem Identification and Definition, Level of Information Gathering, Level of Evaluating Solutions and Developing Approaches, and Level of Implementation Planning stages. Table 3.3 shows the factors' operational definitions and respective descriptions.

Table 3.3 Factors And Respective Operational Definition

Construct	*# of Qs*	Description	*Operational Definition*
λ_1	5	Items related to Problem Identification and Definition	Problem Identification: *Identifying the nature of problems and the goal we want to achieve. (Find out what the problem is?)* *Problem Definition: What information does the problem give us, and what does it ask? And redefine the problem.*
λ_2	*6*	Items related to Information Gathering about problems and solutions	Information Gathering: *Knowing how to find information and identify essential information.*
λ_3	*5*	Items related to Evaluating Solutions and Developing Approaches to problems	Evaluating Solutions and Developing Approaches: *Developing Approaches and Evaluating the likely success of an option in reaction to the demands of the situation.*
λ_4	*3*	Items related to Implementation Planning for problems and solutions	Implementation Planning: *Developing approaches to implementing an idea or solution.*

Reliability: Cronbach's Alpha is conducted and yielded very good results in studies 1 and 2 with 0.92 and 0.89, respectively (Alpha greater than 0.8 and 0.9 is very good and Excellent, respectively)(Russell, 2002).

After completing the EFA procedures, the initial model of the PCPS instrument has been designed – the baseline model. The baseline model consisted of four main factors/constructs and 19 items with 19 corresponding loadings. This multi-vocal model served as the initial model to start CFA procedures. The confirmatory stage has been designed and conducted to test the initial theory from the exploratory stage and, if necessary, whether correct the baseline model or conduct a new model. The next section provides a confirmatory framework along with a detailed illustration of the final structural model of the PCPS instrument.

3.5.1.2 Confirmatory Stage

Confirmatory Factor Analysis (CFA) is applied when researchers have clear hypotheses regarding a specific scale or instrument— the baseline model from the exploratory stage. CFA can be used to test whether the items are related to the hypothesized latent constructs as expected, and also, the model has a sufficient number of latent constructs. If the CFA test finds this relationship, then the model will achieve structural construct validity (Awang, 2012). The inability of the exploratory stage to clearly explain relationships between items with their respective latent constructs makes EFA far less suitable for the purpose of scale development and construct validity (Ahire & Devaraj, 2001). As such, the CFA is found to be more powerful and appropriate for theory and scale development (Ahire & Devaraj, 2001). There are several beneficial software packages that may be used to conduct CFA; while any of the major software packages would work well, Amos 25.0 was selected for its ease of use and user interface.

3.5.1.2.1 Confirmatory Factor Analysis Procedure

The CFA application is comprised of six steps. It starts from model specification, followed by model identification, parameter estimation, the model fit, and finally, the end model is re-specified and compared with other rival models (Bollen & Long, 1993). In this section, the six steps consecutively have been explained. 1) *Model Specification:* is concerned with formulating a model based on a theory and/or previous studies in the field (Awang, 2012). Initial relationships between variables need to be made clear. The initial theoretical model—the baseline model obtained from the exploratory stage-was used in the confirmatory stage. 2) *Model Identification:* is concerned with whether one can derive a unique value for each parameter whose value is unknown (Awang, 2012). The model was identified by constraining four weight coefficients for each of four latent constructs to be equal one. 3) *Parameter Estimation:* its aim is to estimate population parameters by minimizing the difference between the observed and the implied model (Awang, 2012). The Maximum Likelihood method, a widely used method, has been chosen as the estimation method in pursuit of the parameter values that provide the greatest benefit to the observed data. 4) *Construct validity:* it examined the degree to which the proposed model fits the data (Awang, 2012). To attain construct validity, several model fit indices should achieve their respective fitness thresholds. 5) *Model Re-specification:* is concerned with improving the model fit by applying modification. Any decision regarding the model modification must be theoretically defensible (Awang, 2012). After applying all the aforementioned steps to the theoretical model, the base model for the PCPS instrument has been created and then verified. For Study 1 and 2, the following model fits indices respectively achieved: Chi-square/DF (1.96 and 2.06), CFI (.94 and .94), GFI (.91 and .92), RMSEA (.062 and .061), and SRMR (.050 and .052); where values of 5.0 and 3.0 are acceptable and good, respectively for Chi-square/DF, values of .90 and .95 are acceptable and good, respectively for CFI and GFI, and values of .08 and .06 are acceptable and good, respectively, for SRMR and RMSEA(Byrne, 2010; Hair, Anderson, Babin, & Black, 2010; Hu & Bentler, 1999; Meyers, Pourbohloul, Newman, Skowronski, & Brunham, 2005).

3.5.1.2.2 Model Comparison

After the construct validity (model fit) has been achieved, the last step of CFA (that is, model comparison) was performed. 6) *Model comparison:* it tests the sufficient number of factors (constructs) and respective observed variables for those factors (the structural model). If a scale were originally posited as containing multiple distinct factors (constructs), the measurement models should directly test this by comparing the fit of that model with more parsimonious nested models, including 1-factor, 2-factor, 3-factor models and etc. Two models are nested if one is derived from the other one by placing restrictions on it. Since the base model is originally a 4-factor model, all the best 3-factor, 2-factor, and 1-factor models derived from the base model were all nested to each other. a) the best *3-factor model* was nested with the new model and had one more constraint than the new model; the correlation between third and fourth factors constrained to be one (these two factors constrained to be totally dependent on each other). b) the best *2-factor model* was nested with the new model and had two more constraints than the base model, including the covariances among first, third, and fourth factors constrained to be one; i.e., all first, second, and third factors served as one single factor. The best 1-factor model was the original model in which all the covariances among four factors were constrained to be one. Chi-square difference test was conducted based on the below formula (that is, Equation 3.1), and the results of these tests shown in Table 3.4:

$$\text{Chi-square difference test} = \chi^2 \text{ (model with fewer factors)} - \chi^2 \text{ (model with more factors)/(DF (fewer factor model) – DF (more factor model))} \tag{3.1}$$

The null and alternative hypothesis for all the following model comparisons using Chi-square difference test was:

H_0comparison: There was no statistically significant difference between the base model (4-factor) and the fewer factor model, and the addition of the additional factor did not significantly improve the fit to the data; therefore, the base model is not preferred to the fewer factor model.

H_1comparison: There was a statistically significant difference between the base model (4-factor) and the fewer factor model, and the addition of the additional factor did significantly improve the fit to the data; therefore, the base model is preferred to the fewer factor model.

Table 3.4 Comparisons of The Base Model with Nested Rival Models

	Comparison between the base model and	$\Delta\chi^2$	ΔDF	*P*-value	Result	Decision
Study 1	The best 3-factor model	82.8	1	< 0.001	Reject H_0	The base model selected
	The best 2-factor model	114.0	3	< 0.001	Reject H_0	The base model selected
	1-factor model	131.5	6	< 0.001	Reject H_0	The base model selected
Study 2	The best 3-factor model	48.1	1	< 0.001	Reject H_0	The base model selected
	The best 2-factor model	68.3	3	< 0.001	Reject H_0	The base model selected
	1-factor model	103.8	6	< 0.001	Reject H_0	The base model selected

According to Table 3.4, the statistical significance test for the difference between the base model and, respectively, 1-factor, the best 2-factor, and the best 3-factor models resulted in the rejection of the null hypotheses for both first and second studies. In other words, the deduction of the factors did not significantly improve the fit to the data; therefore, the base model was preferred to the other rival nested models. This result emphasized that the sufficient number of factors for the CPSP instrument was four factors, which is the base model. The base model served as the final model for the CPSP instrument in measuring complex problem-solving preferences of individuals in the domain of complex systems.

3.5.1.3 The Final Model

After conducting the Chi-square difference test to verify the sufficient number of factors for the PCPS instrument, the base model was selected as the final model of the study. Table 3.5 shows the structure of the final model with respective factor loadings. The final model consisted of four distinct factors (constructs) and 17 items (questions), which measure different individual's perceived complex problem-solving. Validity and reliability features of the final model were demonstrated below:

Table 3.5 The final model of PCPS Instrument After Exploratory and Confirmatory Stages for Practitioners and Students.

Factors	Item	Factor Loading
Problem Identification and Definition	Item 1	.7[.7]
	Item 2	.6[.5]
	Item 3	.7[.8]
	Item 4	.5[.6]
Information Gathering	Item 5	.7[.7]
	Item 6	.6[.7]
	Item 7	.6[.5]
	Item 8	.2[.5]
	Item 9	.7[.7]
	Item 10	.9[.8]
Evaluating Solutions and Developing Approaches	Item 11	.7[.8]
	Item 12	.7[.6]
	Item 13	.6[.6]
	Item 14	.6[.6]
Implementation Planning	Item 15	.7[.6]
	Item16	.8[.8]
	Item 17	.8[.9]

**Note: the factor loadings outside the brackets belong to PRACTITIONERS and inside the bracket belong to STUDENTS.*

1) *Construct validity*: For sample study 1 and sample study 2, the following model fits indices respectively achieved: Chi-square/DF (1.96 and 2.06), CFI (.94 and .94), GFI (.91 and .92), RMSEA (.062 and .061), and SRMR (.050 and .052); where values of 5.0 and 3.0 are acceptable and good, respectively for Chi-square/DF, values of .90 and .95 are acceptable and good, respectively for CFI and GFI, and values of .08 and .06 are acceptable and good, respectively, for SRMR and RMSEA (Byrne, 2010; Hair et al., 2010; Hu & Bentler, 1999; Meyers et al., 2005). The construct validity's result suggested that the final model fitted the data well and was able to measure what was intended to measure.
2) *Uni-dimensionality*: This will be achieved when all measuring items have acceptable factor loadings for the related factor (George & Mallery, 2003). The sample size of this study was between 200 and 400, and according to Field (2000, pp. 440), factor loading greater than 0.4 on one factor demonstrates an acceptable relationship. As shown in Table 3.5, all the factor loading had acceptable and excellent factor loading. Therefore, the final model for both studies was achieved the uni-dimensionality criterion.
3) *Discriminant Validity*: The covariance greater than 0.85 between two factors indicates the two factors are redundant or experiencing a serious multicollinearity problem (Awang, 2012). Additionally, all the covariances between factors in the final model were below .85. Therefore, the final model had discriminant validity among its factors.
4) *Composite Reliability (CR):* indicates the reliability and internal consistency of a latent factor (construct). The final model has achieved the CR criterion (CR > .7 and .8 are good and excellent, respectively) for all four factors (see Table 3.6)(Tseng, Dörnyei, & Schmitt, 2006).

Table 3.6 Composite Reliability Results for the Final Model

Factors	Problem Identification and Definition	Information Gathering	Evaluating Solutions and Developing Approaches	Implementation Planning
Study 1	0.71	0.78	0.75	0.80
Study 2	0.73	0.80	0.74	0.79

As has been discussed above, the final model respected all criteria of construct validity, uni-dimensionality, discriminant validity, and composite reliability. As a result, the main null hypothesis of the study (*H_0main*) was supported. *There is no statistically significant difference between the final model of the PCPS instrument and the actual data model in order to measure the state of perceived complex problem-solving at the individual level; i.e., the final model of the PCPS instrument fits the data well and is able to measure the state of perceived problem-solving at the individual level*.

3.5.2 Structural Equation Modeling (SEM)

3.5.2.1 Study Variables

The variables listed below are developed in the proposed theoretical model (see Figure 3.3)

3.5.2.1.1 Latent Independent Variable

The "Systems Thinking Skills Preferences" is an abstract theoretical variable and cannot be directly measured; therefore, we used a latent variable (unobservable variable) to indirectly measure it through the seven observed variables associated with the seven dimensions of the systems thinking instrument. This latent variable indirectly measures the individuals' overall systemic skills preferences based on the seven dimensions, which resulted from an extensive systematic review using grounded theory in the domain of complex systems. The seven dimensions are 1) level of *Complexity*, 2) level of *Independence*, 3) level of *Interaction*, 4) level of *Change*, 5) level of *Uncertainty*, 6) level of *Systems Worldview*, and 7) level of *Flexibility.* Figure 3.1 indicates the detailed definition of each dimension with a simple description of each.

3.5.2.1.2 Latent Dependent Variable

To assess individuals' Perceived Complex Problem-Solving the study utilized the PCPS instrument with its four stages 1) Level of Problem Identification and Definition, 2) Level of Information Gathering, 3) Level of Evaluating Solutions and Developing Approaches, and 4) Level of Implementation Planning dimensions. These four dimensions, which are condensed into one latent variable called Perceived Complex Problem-Solving, are used as a problem-solving perception indicator for the study's population.

Before interpreting the results of the study, the proposed theoretical model needs to be validated through the establishment of construct validity. As mentioned, the proposed theoretical model shows the structural relationship between dependent and independent latent variables (that is, systems thinking skill Preferences and PCPS) through the regression and measurement weights.

The construct validity of the theoretical model is obtained through the investigation of model fit indices. The fit indices values indicated that the proposed theoretical model obtained the construct validity and measured what it is intended to measure; consequently, it is deemed valid to test the study's hypotheses. The construct validity was conducted 1) to show that the proposed theoretical model was able to measure what it is intended to measure (i.e., the proposed model fits the data), 2) to show that the associated results of the model can be generalizable, and 3) to test the study hypotheses.

To test the study hypotheses, the proposed theoretical model was tested through structural equation modeling using AMOS software version 25.0. The standardized solution for the theoretical model consists of the full structural model used to assess all the relationships among the study's variables (see Figure 3.3).

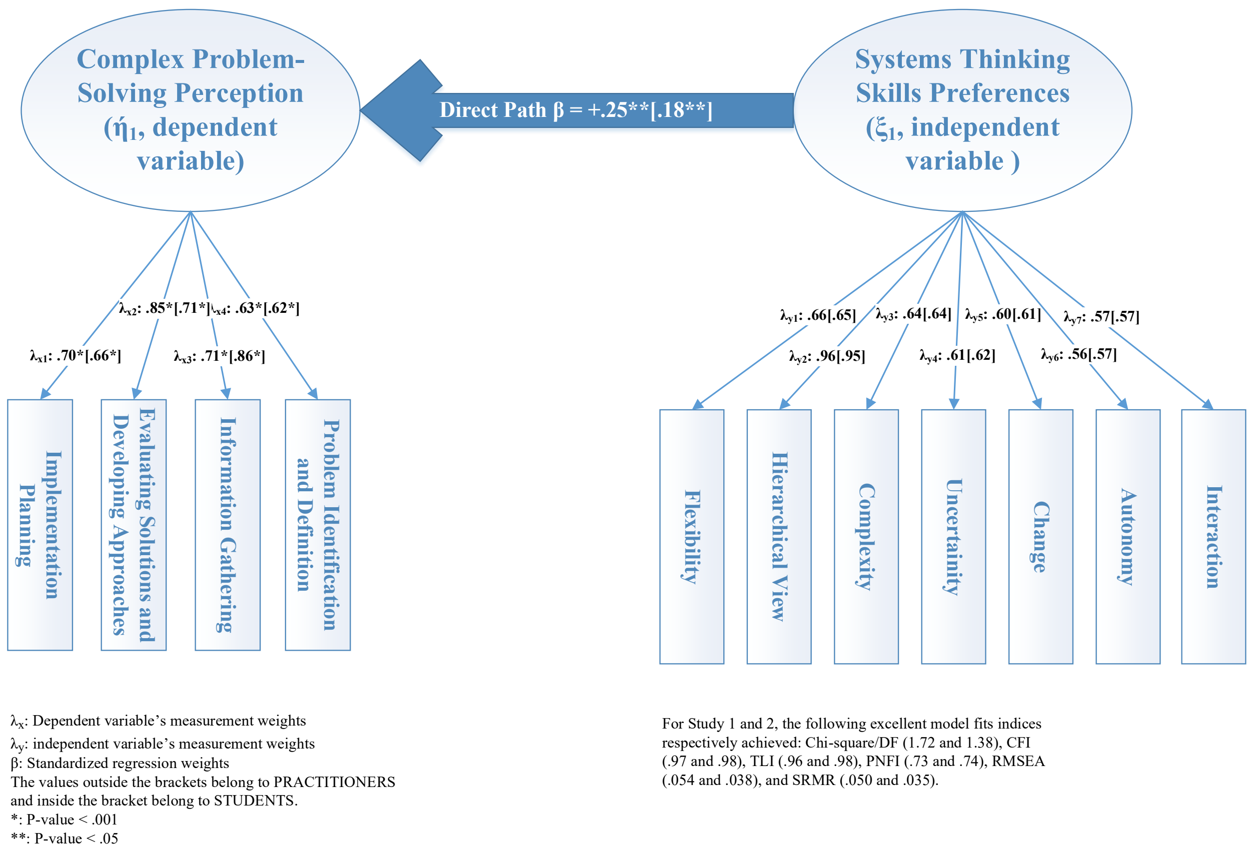

Figure 3.3 The Full Structural Model Analysis of the Proposed Theoretical Model for Both Samples of Practitioners and Students.

As seen in Figure 3.3, practitioners/students with high scores on the systems thinking dimensions of levels of *Complexity*, *Independence*, *Interaction*, *Change*, *Uncertainty*, *Systems Worldview*, and *Flexibility* also have high scores on four stages of PCPS, including 1) Level of Problem Identification and Definition, 2) Level of Information Gathering, 3) Level of Evaluating Solutions and Developing Approaches, and 4) Level of Implementation Planning dimensions. For example, a practitioner/student with a high score in the Level of Problem Identification and Definition dimension indicates his/her better understanding and defining the problems, and a practitioner/student with a high score in the *Complexity* dimension indicates his/her clear skill preference toward *Complexity* compared to *Simplicity* (see Figure 3.1). The Practitioners with low scores on the seven dimensions of systems thinking skills preferences are associated with low scores on the four stages of perceived complex problem-solving.

Since the relationship between the systems thinking Skills Preference and Perceived Complex Problem-Solving latent variables is significant with p-value < 0.001 (t-value = 3.31) and standardized regression weight of $\beta_1 = +0.25$ (with the standard error of 0.03) for practitioners in study 1 and with p-value of 0.013 (t-value = 2.47) and standardized regression weight of $\beta_1 = +0.18$ (with the standard error of 0.003) for students in study 2, *the main hypothesis* is supported. This indicates that the systems thinking skills preferences of practitioners/students have a positive relationship with their perceived complex problem-solving. In other words, the systems thinking of practitioners/students affects their perception in solving complex problems.

3.6 Concluding thoughts

The competitive environment, rapid changes, and the expansion of communication have led organizations to complex systems with multiple relationships. In such situations, complex challenges and problems have arisen, and as a result, the ability to solve complex problems is a necessary competency for an individual and organization. Therefore, complex problem-solving has been considered in numerous international evaluations both in the field of education and in the industry.

In *Phase I* of the study, the literature about the history, definitions, and process of complex problem-solving were reviewed. Most assessments of complex problem-solving were using computer simulations, and there was no questionnaire for professional assessment with regards to other questionnaires like personality, critical thinking, and performance. Although several typical problem-solving questionnaires were designed in specific areas regardless of the simplicity or complexity of the problem, a questionnaire based on complex problem-solving theories does not exist. As a result, To bridge this literature gap, a questionnaire was designed in *Phase II*. In this phase, based on theories and processes, four main stages were derived, and 32 phrases were designed for the purpose of assessing the level of general knowledge and understanding of people about complex problems and the processes needed to solve them. Then, in *Phase III*, after gathering experts' feedback and ideas, 19 items were chosen, and the PCPS instrument was developed. The *content validity* of the questionnaire (the relevance of the item, simplicity of the item, and the clarity of the item) was evaluated by ten university faculties and experts in the field of public administration, and all 19 questions were accepted with CVI> 0.7. The main purpose of this phase was to determine the capability of the instrument to capture an individual's perception in complex problem-solving.

Along with using the PCPS instrument to gather data, the scale development of the instrument was started in *Phase IV*. In the data collection of two studies, 250 managers and 373 students from different races, gender, educational backgrounds, and occupations have participated in the experiment. This dataset had no missing value and passed normality test criteria. Some comprehensive scale development techniques were performed in two stages called the *exploratory stage* and the *confirmatory stage.* To shape the initial theoretical model, the dataset has been analyzed in the exploratory factor analysis framework and resulted in the initial theoretical model called the baseline model. To make the final decision about the number of factors, after checking Eigenvalues and the Scree Plot, four factors retained with eigenvalues greater than one, including Level of Problem Identification and Definition, Level of Information Gathering, Level of Evaluating Solutions and Developing Approaches, and Level of Implementation Planning.

After attaining the initial theory of the PCPS instrument, the confirmatory stage began to test the initial theoretical model. In the Confirmatory stage, the baseline model was tested and modified through the CFA framework. After completing six main steps of CFA, the best-fitted model to the dataset called *the final model was retained*. The final model consisted of four distinct factors (constructs) and 17 items (questions), which measure different individual's perceived complex problem-solving. The final model had the best theoretical and logical support along with good construct validity and reliability results, and it will service as the validated theoretical model for the PCPS instrument and will measure the level of perception of individuals in complex problem-solving.

The PCPS tool presented in this study allows for better understanding with regards to individual's perceived complex problem-solving. The application of this instrument is broad with usefulness in industry, education, and government and will allow management/superiors to identify the strengths and weaknesses of an individual in terms of cognitive thinking. So, for further research in this study, the tool has been used to assess the relationship between an individual's systems thinking preferences and his/her perceived complex problem-solving. Base on testing, *the main hypothesis* is supported. This indicates that the systems thinking skills preferences of practitioners/students have a positive relationship with their perceived complex problem-solving. In other words, practitioners/students with high scores on the systems thinking dimensions of levels of *Complexity*, *Independence*, *Interaction*, *Change*, *Uncertainty*, *Systems Worldview*, and *Flexibility* also have high scores on four stages of PCPS, including 1) Level of Problem Identification and Definition, 2) Level of Information Gathering, 3) Level of Evaluating Solutions and Developing Approaches, and 4) Level of Implementation Planning dimensions. The contribution of this hypothesis is consistent with other studies such as Sweeney and Sterman (2000), who developed a list of systemic thinking features to assess students' capability in complexity. Kinteng, Kaufman, and Dreyer (2001) showed systems thinking could provide a framework for analyzing and solving complex issues in the management of today's organizations. Mani and Maharaj (2002) showed systems thinking has a relationship with performance in complex problem-solving. As they mentioned, system thinking aids in understanding the structure of a problem and then would lead to better performance.

3.6.1 Future studies and limitations

This tool does not directly assess problem-solving ability but rather examines the level of perception of individuals from complex problems and complex problem-solving processes. The higher a person's score in PCPS, the better their knowledge and understanding of complex problem-solving and its process for achieving more effective results. This test does not ask the participants about a hypothetical and specific situation and neither designed for a specific setting like management or education, etc., so it can be used in different settings wherever individual needs to deal with complex problems. For this goal, further research by investigating many ways of applying the tool in a more interactive setting and comparing new and old results for improving the reliability of the instrument further.

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CHAPTER IV

THE IMPACT OF PRACTITIONERS' PERSONALITY TRAITS ON THEIR LEVEL OF SYSTEMS-THINKING SKILLS PREFERENCES

Nagahi, M., Jaradat, R., Goerger, S. R., Hamilton, M., Buchanan, R. K., Abutabenjeh, S., & Ma, J. (2021). The impact of practitioners' personality traits on their level of systems-thinking skills preferences. *Engineering Management Journal*, *33*(3), 156-173. https://doi.org/10.1080/10429247.2020.1780817

4.1 Abstract

In this study, we used a structural equation modeling method to investigate the relationship between systems engineers and engineering managers' Systems-Thinking (ST) skills preferences and their Personality Traits (PTs) in the domain of complex system problems. As organizations operate in more and more turbulent and complex environments, it has become increasingly important to assess the ST skills preferences and PTs of engineers. The current literature lacks studies related to the impact of systems engineers and engineering managers' PTs on their ST skills preferences, and this study aims to address this gap. A total of 99 engineering managers and 104 systems engineers provided the data to test four hypotheses posed in this study. The results show that the PTs of systems engineers and engineering managers have a positive impact on their level of ST skills preferences and that the education level, the current occupation type, and the

managerial experience of the systems engineers and engineering managers moderate the main relationship in the study.

Keywords: Systems-Thinking Skills Preferences, Myers-Briggs Type Indicator (MBTI), Complex Systems, Moderation Model, Structural Equation Modeling.

4.2 Introduction

Practitioners such as engineering managers and systems engineers have to address the increasing challenges of today's socio-technical systems while maintaining and elevating performance under increasing complexities and pressures to reduce workforce, resources, and costs. These challenges include (Ackoff, 1995; Boardman & Sauser, 2006; Keating, 2008): 1) a high level of *integration* where systems are combined operationally, managerially, or geographically to produce new goals, 2) *ambiguity* stemming from a lack of clarity to support decisive action and commitment to alternative courses of action, 3) *uncertainty* caused by incomplete knowledge of systems and the unintended consequences they experience, and 4) *interdependence* where there is mutual influence among systems and their related elements making analysis difficult. These four elements are likely to escalate as we grapple with the interdisciplinary system problems of the 21st century, which blur the lines between technical, social, organizational, managerial, and policy considerations (Boardman & Sauser, 2006; Churchman, 1968, 1971, 1979; Deming, 1982; DeLaurentis, 2005; Drucker, 1954, 2012a,b; Gorod, Sauser, & Boardman, 2008; Jaradat, Keating, & Bradley, 2018). Ackoff (1971, 1995) clarified that in treating complex system problems, the focus should be on the whole system and not the parts. In response to these challenges, it is necessary to develop qualified practitioners who can take a more holistic “systemic” approach when dealing with complex system problems, as suggested by Churchman’s (1968) book “The Systems Approach.”

In addition to the importance of systems thinking in the domain of complex systems, there is an increasing trend in social-personality psychology research devoted to understanding how an individuals’ personality traits, preferences, cognition, and social behavior can affect how they address complex system problems (Brown & Moskowitrz, 1998; Freeman, Dale, & Farmer, 2011; Schmidt & Richardson, 2008; Schuldberg & Gottlieb, 2002; Spivey, 2007; Vallacher, Read, & Nowak, 2002; Warren, 2006). For example, Mumford and his colleagues (2000) suggested that an individual’s PTs might have an impact on his/her leadership ability in dealing with complex systems problems. According to the socio-technical systems theory, “Socio-technical system design is based on the premise that an organization or a work unit is a combination of social and technical parts and that it is open to its environment” (Appelbaum, 1997, p. 453). Organizations need a joint optimization design to more effectively handle complexity, emergence, and turbulence in a work environment (Appelbaum, 1997; Jaradat et al., 2019). The systems thinking paradigm, in conjunction with systems theory laws and principles and socio-technical systems theory, is the basis for the proposed theoretical model for testing the four hypotheses of this study.

Failures in socio-technical systems can result from non-technical as well as technical elements and can be related to organizational and individual issues where individuals are an essential contributor to the failure. These failures can be classified as having socio-technical aspects stemming from both technical and social, policy, politics, and power elements as well as interactions between those elements (Ackof, 1971, 1994, 1995;; Jaradat et al., 2018; Katina, Keating, & Jaradat, 2014; Frank, 2006; Clegg, 2000; Checkland, 1981). Practitioners’ ST skills preferences are necessary for the development of rigorous solutions to avoid these failures in socio-technical systems. Thus, studying the practitioners' ST skills preferences creates several combinations that lead to the effective management of complex multidimensional systems. For example, the assessment of ST skills preferences can help engineering managers to build engineering teams with specific skillset preferences and then effectively match their skillsets with the appropriate problem-solving technique to minimize the waste of workforce and resources and reduce costs. Similarly, Deming (1982), in his book "Out of the Crisis," developed a systems-thinking approach that consists of 14 principles for the transformation of American style management. His principles were guided many engineering managers on how to manage the waste of human resources, the products' quality, materials, and machine-time in their organizations.

Although much has been written about systems thinking and personality indicators, few empirical investigations have covered the impact of PTs on systems engineers and engineering managers' ST skills preferences and their implications for systems engineers and engineering managers. This study, which aims to investigate this impact and its implications, focuses on four demographic factors, educational level, current occupational type, managerial experience, and work experience, and will study their effects on the relationship between PTs and ST skills preferences. Systems-thinking skills preferences and PTs might determine how systems engineers and engineering managers respond to different situations in solving socio-technical system problems.

This study is essential for researchers and academics because it will address two main gaps in the literature. First, it will provide data to address the literature gap in the complex system domain by presenting comparisons and potential relationships between systems engineers and engineering managers' ST skills preferences and personality traits. Second, by considering the impact of demographic factors such as educational level, current occupation type, managerial experience, and work experience, the study could show that these factors do affect a systems engineer and engineering manager's PT and ST skills preferences. In this study, we have developed four main hypotheses based on the literature. To test these hypotheses and to investigate these relationships and comparisons, a valid ST skills preferences instrument (Jaradat, 2015; Jaradat et al., 2018) and the Myers Briggs Type of Indicator's (MBTI) instrument (Keirsey & Bates, 1984) are used in this study.

The development of the research hypotheses is presented below and is followed by the research design and methodology, and the different analysis techniques, including structural equation modeling, used to investigate the validity and reliability of the theoretical model. The paper concludes with a discussion, implications, and future research.

4.3 Background and Hypotheses Development

A thorough review of the literature from the 1980s to 2018 revealed that there had been several studies focused on the following research areas: (1) the theory of systems thinking (Ackof, 1994; Checkland, 1981,1999; Jaradat et al., 2018; Senge, 1991, 2004), (2) systems dynamics (Gorod, Sauser, & Boardman, 2008; Keating et al., 2003), (3) the role of systems thinking in solving complex system problem domains (Checkland, 1981,1999; Deming, 1982; Drucker, 2012a,b; Lawrence et al., 2019), (4) the systems approach (Ackof, 1995; churchman, 1968,1979; Hossain et al., 2019a,b), and (5) comparisons of different ST tools used primarily in education (Frank, 2006; Lawrence et al., 2019; Richmond, 1993; Stirgus et al., 2019). For example, Senge (1991) defined systems thinking as "a conceptual framework, a body of knowledge and tools that have been developed over the past fifty years, to make the full patterns clearer, and to help us see how to change them effectively" (P.7). This section will focus on introducing the ST survey instrument and personality assessment tool used for data collection.

The ST skills preferences instrument (with $\alpha = 0.81$), developed by Jaradat (2015) and Jaradat et al. (2018), measures individuals' ST skills preferences in dealing with complex system problems. This instrument uses seven dimensions (see Table 4.1), which were developed using grounded theory coding. The instrument consists of 39 binary questions culminating in seven preferential categories/systems skills dimensions that determine an individual's inclination toward a Holistic or Reductionist thinking skills preferences profile. By taking the instrument, each participant obtains a profile consisting of seven scores and seven letters corresponding to the seven ST dimensions.

Myers and Briggs, who were inspired by Jung's psychological types, developed an instrument called "The Myers-Briggs Type Indicator." The MBTI instrument is considered "one of the most comprehensive theories explaining human personality" (Tucker & Kroeger, 2010, p. 22; Myers, 1962; Myers & McCaulley, 1985). The MBTI construct consists of four main scales. The *Extraversion-Introversion* scale describes energy utilities. The *Sensing-Intuition* scale describes perception. The third scale, *Thinking-Feeling,* describes judgment, and the last scale, *Judging-Perceiving,* describes an orientation.

Comparing the definition of the ST skills preferences dimensions (shown in Table 4.1) and the four MBTI dimensions, there are hypothetically some linkages between the two. The *Sensing-Intuition* scale of the MBTI corresponds to the *Systems world view*, *Complexity*, and *Uncertainty* dimensions of the ST skills preferences instrument; the *Extraversion-Introversion* scale and the *Interaction* and *Independence* dimensions show similar characteristics; linkage can also be seen between the *Judging-Perceiving* scale and *Flexibility* and *Change* dimensions and between the *Thinking-Feeling* scale and *Systems worldview* and *Uncertainty* dimensions. Based on the literature, we can also hypothesize that demographic factors such as education level (Assaraf &

Orion, 2005; Bawden, Macadam, Packham, & Valentine, 1984; Betts, 1992; Dolansky & Moore, 2013; Richmond, 1993), current occupation type (Cable & Judge, 2003; Tetlock, Peterson, & Berry, 1993; Williams, 2004; Zhao & Seibert, 2006), and Managerial Experience (Porter, 2008; Bureš & Čech, 2007; Furnham & Stringfield, 1993) might impact the relationship between PTs and the ST skills preferences.

In this study, the MBTI instrument was used to measure systems engineers and engineering managers' PTs, the ST skills preferences instrument was used to measure systems engineers and engineering managers' ST skills preferences, and four demographic factors were added as additional variables to the proposed theoretical model. Details of the development of the hypotheses and the theoretical model are discussed below.

Table 4.1 Seven Dimensions of the "ST Skills Preferences Instrument" (Jaradat, 2015, Fig. 4)

Less Systemic (Reductionist)	Dimension	More Systemic (Holistic)
Simplicity (S): Avoid uncertainty, work on linear problems, prefer the best solution, and prefer small-scale problems.	***Level of Complexity***: Comfort with multidimensional problems and limited system understanding.	**Complexity (C)**: Expect uncertainty, work on multidimensional problems, prefer a working solution, and explore the surrounding environment.
Autonomy (A): Preserve local autonomy, a trend more toward an independent decision and local performance level.	***Level of Independence***: Balance between local-level autonomy versus system integration.	**Integration (G)**: Preserve global integration, a trend more toward dependent decisions and global performance.
Isolation (N): Inclined to local interaction, follow a detailed plan, prefer to work individually, enjoy working in small systems, and interested more in cause-effect solution.	***Level of Interaction***: Interconnectedness in coordination and communication among multiple systems.	**Interconnectivity (I)**: Inclined to global interactions, follow a general plan, work within a team, and interested less in identifiable cause-effect relationships
Resistance to Change (V): Prefer taking few perspectives into consideration, over-specify requirements, focus more on internal forces, like short-range plans, tend to settle things, and work best in a stable environment.	***Level of Change***: Comfort with rapidly shifting systems and situations.	**Tolerant of Change (Y)**: Prefer taking multiple perspectives into consideration, underspecify requirements, focus more on external forces, like long-range plans, keep options open, and work best in a changing environment.
Stability (T): Prepare detailed plans beforehand, focus on the details, uncomfortable with uncertainty, believe the work environment is under control, and enjoy objectivity and technical problems.	***Level of Uncertainty***: Acceptance of unpredictable situations with limited control.	**Emergence (E)**: React to situations as they occur, focus on the whole, comfortable with uncertainty, believe the work environment is difficult to control, and enjoy non-technical problems.
Reductionism (R): Focus on particulars and prefer analyzing the parts for better performance.	***Systems Worldview***: Understanding system behavior at the whole versus part level.	**Holism (H)**: Focus on the whole, interested more in the big picture, and interested in concepts and abstract meaning of ideas.
Rigidity (D): Prefer not to change, like determined plans, not open to new ideas, and motivated by routine.	***Level of Flexibility***: Accommodation of change or modifications in systems or approach.	**Flexibility (F)**: Accommodating to change, like a flexible plan, open to new ideas, and unmotivated by routine.

4.4 Hypotheses Development and the Proposed Theoretical Model

The literature is replete with studies related to the effects of personality theory and systems thinking on organizational outputs; however, there remain essential gaps that warrant further attention (Abbas, Sajid, & Mumtaz, 2018; Bradley & Hebert, 1997; Toshima, 1993; Williamson, Lounsbury, & Han, 2013).

- There is a lack of research investigating the relationship between systems engineers and engineering managers' personality traits (PTs) and their level of systems-thinking (ST) skills preferences in the domain of complex systems.
- There is a literature gap regarding the impact of demographic factors such as education level, current occupation type, managerial experience, and work experience on systems engineers and engineering managers' PTs and ST skills preferences in the domain of complex systems. In other words, there is currently nothing in the literature that simultaneously tests all of the mentioned demographic variables to provide a better understanding of the relationship between systems engineers and engineering managers' PTs and ST skills preferences.

In this study, four hypotheses are tested to address these gaps. The first hypothesis explores the impact of systems engineers and engineering managers' PTs on their ST skills preferences when engaging complex system problems (the main relationship of this study). The second hypothesis involves the moderation impact of systems engineers and engineering managers' education levels in dealing with complex systems. The third hypothesis intends to investigate the impact of systems engineers and engineering managers' current occupation type on the relationship between PTs and ST skills preferences. The fourth hypothesis explores the potential impact of managerial experience on systems engineers and engineering managers' PTs and ST skills preferences. In addition to enriching the current body of literature, testing these hypotheses can provide insights for systems engineers and engineering managers by investigating the relationship between personality traits and systemic skills preferences and studying the impact of this relationship on systems engineers and engineering managers' tendencies in solving socio-technical system problems.

Toshima (1993) emphasized that the intellectual abilities and personality traits of Japanese systems engineers are correlated with their level of performance. Linder and Frakes (2011) investigated the correlation between individuals' personality types using MBTI and 17 important systems thinking practices among members of professional organizations, professionals, and graduate-level students. Their study showed that there are correlations between several systems thinking practices and four dimensions of MBTI assessment. Drucker (1954) introduced a systemic approach "management by objective" to assist organizations in achieving a better quality decision-making process. We are reminded by Keating et al. (2003) and Steward (1981) that conventional planning techniques do not adequately address these complex systems. Engineers and engineering managers are charged with operating in complex systems, often working in a parallel system where multiple tasks are coinciding, as stated by Eppinger (1991). As such, the systems skills preferences and PTs of individual systems engineers and engineering managers are integral in addressing these complex systems.

Buffinton, Jablokow, and Martin (2002) mentioned that the personality traits of team members have a potential role in problem-solving styles and interpersonal dynamics of project teams. Toshima (1993) concluded that both intelligence and personality characteristics affect systems engineers' job performance. Abbas et al. (2018) found a relationship between personality traits and knowledge sharing and innovation among engineers. Williamson et al. (2013), who determined the personality traits for engineers for innovation and technology development, found that engineers followed only two of thirteen personality traits when they were compared with non-engineers. Balkis and Isiker (2005) found a close relationship between different thinking styles and the personalities of university students. Zhang (2000; 2001; 2002) found that the thinking styles and personality traits of university students are related. Dragoni and his colleagues (2011) found a highly positive correlation between executives' cognitive abilities (similar to personality traits) and their strategic thinking competency. In a similar study, Soleimani et al. (2018) found that there is a relationship between MBTI personality type of undergraduate students and their cognitive-metacognitive strategies usage in a reading comprehension test. Davidz and Nightingale (2008) showed that participants' personality characteristics positively affect the development of systemic thinking. Since thinking styles and strategic thinking dimensions are in some aspects similar to ST skills preferences dimensions, we hypothesize that a potential relationship between ST skills preferences and PTs of systems engineers and engineering managers might exist.

H_1: There is a relationship between systems engineers and engineering managers' Systems-Thinking Skills Preferences and their Personality Traits (PTs) in the domain of complex systems.

In his studies, Frank (Frank, 2001; Frank & Elata, 2005; Frank & Kordova, 2009) investigated the correlation between the capacity for engineering systems-thinking and project-based learning of freshman engineering students and senior engineering management students. These studies showed that a student's capacity for engineering systems-thinking could be improved and developed through project-based courses and curricula. Several other studies have investigated the individuals' systemic thinking in different educational levels, such as high school level, undergraduate level, and so on. For instance, Assaraf and Orion (2005) showed the correlation between high school students' systemic capabilities and knowledge in earth system education. Betts (1992) emphasized the need for a systemic approach in elementary and secondary education. *Richmond (1993) investigated* the impact of systems thinking on the educational process, thinking paradigm, and learning tools *in the education systems. Consequently, we hypothesize that systems engineers and engineering managers' education level might have an impact on the main relationship of the study. In this study, the education level of systems engineers and engineering managers was considered as having a doctorate's degree, a master's degree, a bachelor's degree, or other degrees such as high school diploma, associate degree, and some college credits.*

H_2: Systems engineers and engineering managers' education levels moderate the positive effects of Personality Traits (PTs) on their Systems-Thinking Skills Preferences.

Different studies have shown the importance of PTs for various occupations. For instance, various studies found managers with different PTs have differences in their thought processes, leadership styles, and performance (Cable & Judge, 2003; Tetlock et al., 1993; Williams, 2004; Zhao & Seibert, 2006). Wasson (2015) and Frank (2001, 2006) and others have emphasized that systems engineers must have distinct abilities and characteristics to deal with complex system problem domains effectively. Eisner (2008) compared the knowledge and skills required in planning, designing, and constructing complex systems by different practitioners, including systems engineers, engineering managers, and project managers. Results showed that different occupants possess distinct skills, behaviors, and characteristics. Therefore, we hypothesize that:

H_3: Systems engineers and engineering managers' current occupation type moderates the positive effect of Personality Traits (PTs) on their Systems-Thinking Skills Preferences.

Porter (2008) stated that managerial experience affects the level of managers' systems approaches concerning corporate social responsibility issues. Ackoff (1994) emphasized that managers need whether through "a direct experience" or "an abstraction extracted from experience by analysis" to confront "situations that consist of complex systems of strongly interacting problems" (p. 184). He categorized these types of problems as *messes*. Mumford and his colleagues (2000) discussed the impact of a leader's career experience on solving the complex social problems in an organization. Bureš and Čech (2007) emphasized the effect of managerial experience on teaching systems thinking concepts. In their 1993 study, Furnham and Stringfield found a correlation between the MBTI personality traits and the managerial experience of Chinese and European managers at an Asian-based international airport. From these studies, we assume that managerial experience might affect the relationship between systems engineers and engineering managers' PTs and ST skills preferences. To investigate only the impact of systems engineers and engineering managers' managerial experience, we controlled the variable "work experience" in the theoretical model, which will be explained in detail in the study variable section. As a result, we hypothesize that:

H_4: Systems engineers and engineering managers' managerial experience, controlled by their Work Experience, strengthens the relationship between Personality Traits (PTs) and their Systems-Thinking Skills Preferences.

Based on the literature provided and the development of hypotheses, Figure 4.1 provides the proposed theoretical model of the study.

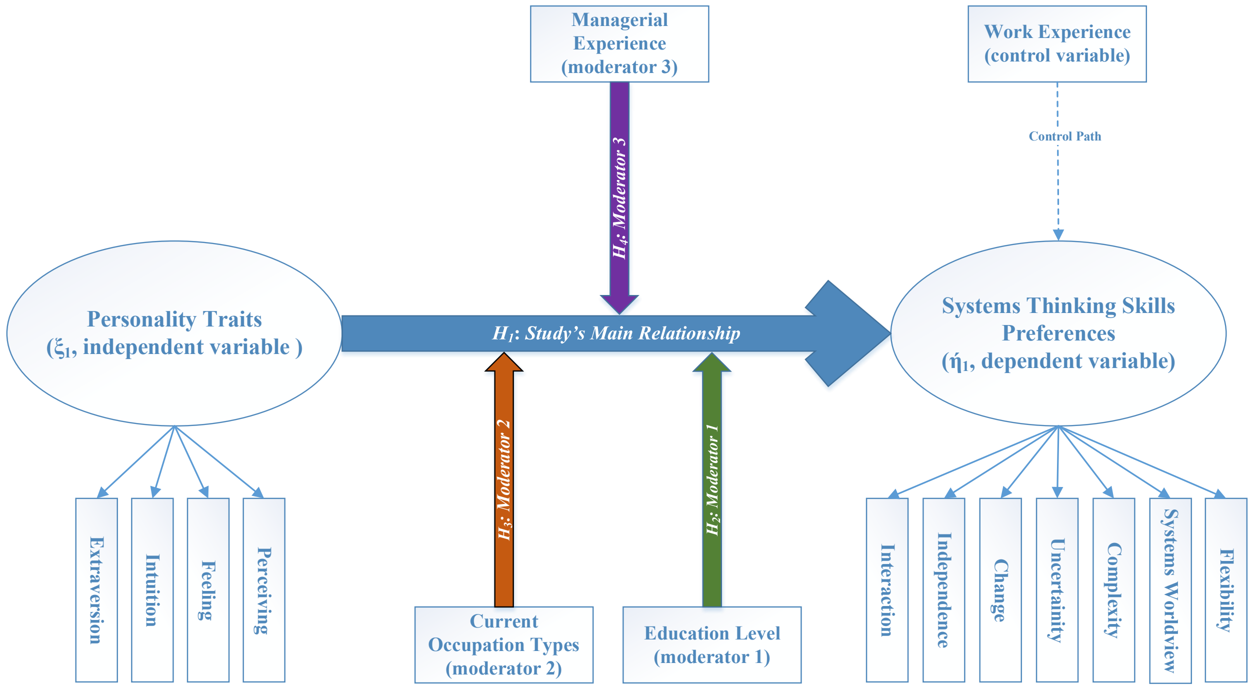

Figure 4.1 The Theoretical Model of the Third Study

4.5 Methodology

The primary objective of this study is to investigate the relationship between systems engineers and engineering managers' PTs and their ST skills preferences through the proposed theoretical model. To test the hypotheses of the theoretical model, the methodology section is divided into three phases: 1) identification of the study sample and data collection procedures, 2) introduction of study variables, and 3) validation of the theoretical model. Figure 4.2 presents the research methodology framework.

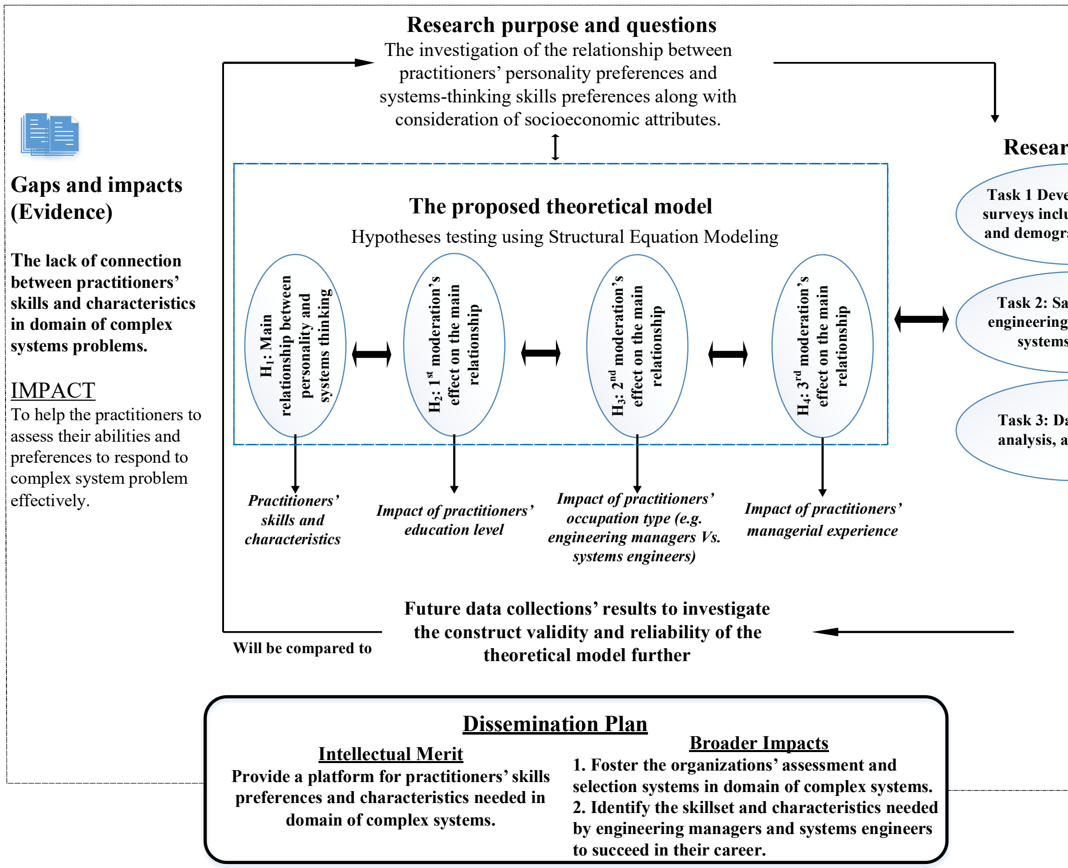

Figure 4.2 The Research Methodology Framework for Third Study

4.5.1 Sample and Data Collection Procedure

The dataset used to test the study hypotheses came from 203 engineering managers and systems engineers working in a complex work environment. The organizations were selected based on one criterion – the complexity of their work environment. To determine the level of work environment complexity, short interviews with several senior managers were conducted. The interview process included four main questions to answer how complex is the work environment based on the complex system attributes such as uncertainty (incomplete knowledge of complex systems and unexpected influences that add uncertainty), lack of clarity (due to the variable nature of a complex system, there can be uncertainty when deciding how to take actions and make decisions.), emergence (because complex systems cannot be predicted, there are often unexpected behaviors or patterns that can only be seen after they occur.), interdependence (complex systems are marked by the interactions between various components of the system).

The types of questions were open-ended questions and close-ended questions. For example, a question was asked—Please describe your work environment in terms of keeping up with changes in the production lines. Another question was about how large the scale of their systems is. Nvivo was used as a tool to collect the interview dataset. Nvivo was also used to scripting the interview' questions. Based on the interviews, twelve organizations were defined as organizations with a complex work environment and were included in the study. The distribution of organizations that were a source for the data is as follows: military and defense agencies (n =5), manufacturing (n = 3), service (n= 2), and systems engineering consultants (n = 2). To test the hypotheses, four demographic factors were collected and included educational levels, current occupation type, managerial experience, and work experience (see Table 4.2).

Based on the literature, there are many recommendations with regard to the sample size needed for an effective SEM analysis. A general rule of thumb is that a "critical sample size" of 200 provides a stable parameter estimate and has sufficient power to test a model. We searched further in the literature and found that one of the most common recommendations for sample size is provided by Nunnally and Bernstein's (1994) rule of 10, which indicates that we should have 10 observations for each indicator in our model. According to the study's theoretical model, shown in Figure 4.1, there are 15 indicators including, four independent variables (MBTI dimensions), three interactional terms (namely, education level, current occupation type, and managerial experience), one control variable (work experience), and seven dependent variables (7-dimensions of ST skills). Consistent with Nunnally and Bernstein's rule of 10, the necessary sample size of the study should be 150, while the actual sample size of the study is 203.

Additionally, Bentler and Chou (1987) argue that an accurate sample size calculation should be based on free parameters of the model where we should have at least five cases for each parameter estimate (including error terms as well as path coefficients). In our proposed theoretical model, we have 16 path coefficients (four λ_{xi}, seven λ_{yj}, and five β_k) and 12 error terms, and according to Bentler and Chou's suggestion, we need 140 samples. The sample size of the study is 203. In conclusion, the selected sample size of the study is consistent with three well-known recommendations in the literature. Moreover, the selected sample size is consistent with the parsimonious fit provided for the study's theoretical model.

An email invitation to participate in the study was sent to the targeted organizations, along with a web-link survey. The respondents filled out the demographic questions and the 39-question ST skills preferences instrument in approximately 10 minutes. Some participants took more than 10 minutes to fill out the survey, but not exceed 15 minutes.

A few days later, a follow-up email sent to the participants to complete the second survey. It took approximately 17 minutes to complete the 70-question MBTI instrument adopted by Keirsey and Bates (1984). The reason for collecting data in two different periods was to reduce the possibility of the common method bias in the data collection phase. The survey's response rate was 55 percent, which resulted in a total of 203 completed responses from systems engineers and engineering managers. Responses were recorded using Qualtrics, and identity confidentiality was assured according to the IRB protocol. Prior to analysis, common method bias was tested in the confirmatory study, and the associated result indicated that common method bias is not a substantial concern in the study.

Table 4.2 Sample Characteristics

Demographic information		Sample size classified by occupation type: Engineering managers	Systems engineers
Occupation type		99	104
The education level	Doctorate	8	17
	Master	63	58
	Bachelor	18	24
	Others	10	5
managerial experience (years)	5 and below	14	13
	6 to 10	17	12
	11 to 15	8	11
	16 to 20	15	11
	21 and above	45	57
work experience (years)	5 and below	1	2
	6 to 10	6	6
	11 to 15	6	5
	16 to 20	4	2
	21 and above	82	89

Note: Others refer to those who have completed some college credit/high school diploma/training associate certificate

Figure 4.3 shows the frequency of different personality type profiles found in the study's sample. The personality type profile with the highest frequency among engineering managers is ISTJ with 37.2 percent, and the second and the third highest are ESFJ and ESTJ with 19.2 and 17.9

percent. These three profiles account for 74.4 percent of all engineering managers' personality type profiles. For systems engineers, ESTJ is the most frequent profile with 35.4 percent, and ISTJ and ESFJ are the second and third most frequent with 30.5 and 14.6. These three profiles include 80.5 percent of systems engineers' personality profiles. The results were consistent with studies of Keirsey and Bates (1984) and Wideman (1998), whose studies categorized ISTJ and ESTJ managers as leaders and ESFJ managers as both leaders and followers. Additionally, McCaulley (1990), Schneider, Smith, Taylor, and Fleenor (1998), and Krumwiede and Lavelle (2000) identified the two most frequent personality type profiles of American managers in business and industry as the ISTJ and ESTJ profiles.

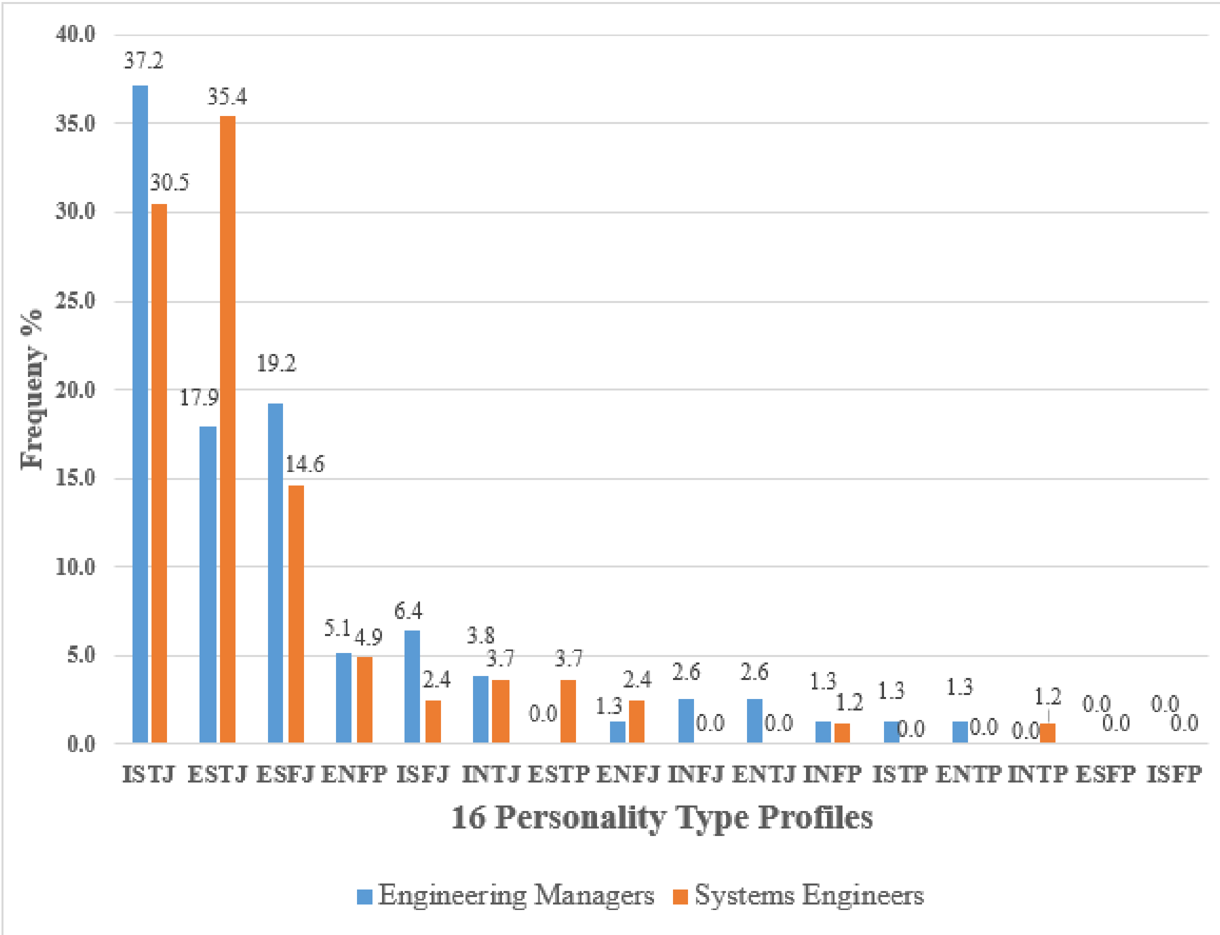

Figure 4.3 The Personality Type Profiles of Engineering Managers and Systems Engineers

4.5.2 Study Variables

The variables listed below are developed in the proposed theoretical model (see Figure 4.1)

4.5.2.1 Latent Dependent Variable

The "Systems Thinking Skills Preferences" is an abstract theoretical variable and cannot be directly measured; therefore, we used a latent variable (unobservable variable) to indirectly measure it through the seven observed variables associated with the seven dimensions of the ST instrument. This latent variable indirectly measures the practitioners' overall systemic skills preferences based on the seven dimensions, which resulted from an extensive systematic review using grounded theory in the domain of complex systems. The seven dimensions are 1) level of *Complexity*, 2) level of *Independence*, 3) level of *Interaction*, 4) level of *Change*, 5) level of *Uncertainty*, 6) level of *Systems Worldview*, and 7) level of *Flexibility.* Table 4.3 indicates the detailed definition of each dimension with a simple description of each. The latent variable, which will be used to assess a practitioner's overall systemic thinking, is called "Systems Thinking Skills Preferences."

Table 4.3 The Detail Definition of Seven Dimensions of ST Skills Instrument with Examples

Dimension	Detail Definition	Simple Description
Level of Complexity	This level describes an individual's inclination to work in complex systems. Complexity and simplicity are notated as (C) for Complexity (S) for Simplicity. • Appreciate and assess the degree of complexity (no full control). • Have the ability to distinguish the characteristics of complex system problems and understand the limitations of traditional systems engineering. • Identify and address the external influences that constrain the complex problem domain. • Be able to align between the nature of the problem, the methodology taken, and the context where complex systems operate. • Grasp multidisciplinary problems.	If an individual is on the "complexity" spectrum (C), s/he probably tends to accept working solutions, enjoys working on problems that have not only technological issues but also the inherent human/social, organizational/managerial, and political/policy dimensions, and expects and prepares for unexpected events. In contrast, if an individual is on the "simplicity spectrum" (S), s/he probably prefers to work on problems that have clear causes, prefers one best solution to the problem, and enjoys working on small scale problems
Level of Independence	The second pair of preferences deal with the level of autonomy and describes an individual's comfort level in dealing with integration. Autonomy and integration are notated as (G) for integration or (A) autonomy. • Appreciate and embrace autonomy. • Draw the difficulties autonomy brings to the complex problem domain. • Balance the tension between autonomy and integration. • Possess the ability to bargain and negotiate to address complex systems objectives.	An individual might find that s/he agrees with some of the attributes under the "autonomy" preference as well as with some attributes under "integration" preference. This could be quite true and natural. If an individual often leans toward making independent decisions, s/he still might tend to make dependent decisions in certain kinds of problems even though s/he actually prefers making independent decisions.
Level of Interaction	The third pair of preferences, which pertains to the level of interaction, describes the type of work environment an individual would prefer, either (I) Interconnectivity or (N) Isolation. • Identify and understand the purpose of integration. • Orchestrate and possess the ability to work across heterogeneous systems (i.e., people and culture). • Provide inputs to identify new risk behaviors and areas where changes need to be considered. • Possess interdisciplinary knowledge. • Pay close attention to the interactions and interdependencies among the systems from a holistic viewpoint. • Coordinate (teamwork), communicate (sharing data and information), and work closely (with other heterogeneous systems) to achieve the overall purpose.	Some individuals might agree with every attribute related to the "interconnectivity" preference and agree with little with "isolation". These individuals would probably lean more toward the "interconnectivity" preference indicating that they enjoy working on problems within a team and are less interested in clear identifiable cause-effect solutions. This does not mean that individuals who prefer to work individually on problems are wrong or somehow inferior; it only shows the different levels of systems thinking with respect to working in complex problem domains.

Table 4.3 (Continued)

Dimension	Detail Definition	Simple Description
Level of Change	The fourth pair of preferences deal with the level of change. This level describes an individual's inclination to make changes when dealing with complex system problems. The preference pairs are notated as (Y) for tolerant of change and (V) as resistance to change. • Trace and map the ongoing change in needs, technology, and social infrastructure. • Focus on the whole instead of the traditional sequential treatments (life cycle). • Take multiple relevant perspectives into consideration. • Explore the environment and look for new-outside opportunities to deal with the pace growth of complex systems. • Have the ability to distinguish between the SoS need and the system aggregation need. • Be able to formulate rapid shifting solutions.	"Tolerant of change" individuals prefer to work in changing environments while "resistance to change" individuals lean more toward stable environments. Some individuals are likely to consider multiple viewpoints before making a decision, and others assume that these different perspectives could create distractions. Again there are no bad or good systems thinker types; it solely depends on the nature of the problem. If the problem has a large number of stakeholders, it is preferable to assign it to individuals who enjoy working in changing environments.
Level of Uncertainty	The fifth pair of preferences deal with the level of uncertainty and ambiguity. This level describes an individual's preference for making decisions as (E) emergence or as (T) stability. • Identify and inspect all aspects (non-technical) of the problem. • Explore the environment to deal with emergence. • Think in a holistic way and avoid obsession with details. • Prepare by designing for flexibility and adaptability in the system. • Appreciate the high level of uncertainty. • Avoid an optimal solution and consider a range of satisficing solutions.	Individuals who agree with the emergence preference are more likely to focus more on the whole in solving problems instead of using a reductionist technique to focus on specific techniques. If individuals agree with half the "emergence" attributes and half the "stability" attributes, the way they choose to deal with problems is not as clear. To clarify again, there are no good or bad combinations; there are only variations from one individual to another. At this point, at least, this research cannot tell if one combination is better than others.
Level of Systems Worldview	The sixth pair of preferences deal with the level of looking at the problem. This level describes an individual's inclination to looking at the problem in complex systems as (H) holism or as (R) reductionism. • Recognize holism as a new paradigm of thinking. • Identify and assess all aspects of the problem. • See the big picture and understand the system as a whole unit. • Focus on the whole and avoid looking at the tiny detail. • Demonstrate an understanding of the laws and principles relevant to the problem under study. • Treat the problem as a whole and avoid thinking in the "cause and effect" paradigm.	An individual whose answers fall into the (H) category is probably more interested in big picture concepts and ideas than his (R) counterpart, who would prefer to focus on particulars and details. However, the nature of complex system problems, their context and surrounding environment determine the way a problem should be managed. In some problems focusing on the parts is vital for determining the right –best solution, but for other problems, this technique might worsen the overall performance of the system.
Level of Flexibility	The last pair of preferences deal with the level of flexibility. This level describes an individual's preference for making decisions as (F) Flexibility or as (D) rigidity. • Appreciate the importance of flexibility and adaptability as functions to deal with emergence and uncertainty. • Recognize the importance of having a flexible design to add, adjust or remove any of the systems' components. • Remain open to all ideas. • Encourage the dissemination of plans and ideas. • Possess the ability to accommodate any changes or modifications in ensemble systems.	An individual may find her/himself displaying attributes from both preferences with perhaps a clear predisposition toward the "emergence and complexity" preferences but also a slight tendency toward the "flexibility" preference.

The score calculation for each of the seven dimensions of ST skills preferences is conducted as follows. Each dimension of the ST skills instrument has five binary questions (in some dimensions, six binary questions). Each binary question has a more systemic answer (counted and coded one) and a less systemic answer (counted and coded zero). After coding all the binary questions, one aggregate score is calculated for each dimension, which is the sum of the coded binary questions divided by the total number of questions in one dimension. To unify the scores across the seven dimensions, the percentage of each aggregate score is calculated. For example, the complexity dimension consists of six binary questions. The level of *Complexity* is calculated for each respondent, as expressed in Equation (4.1). As a result, each respondent receives an aggregate score for each ST dimension, which ranges from 0% to 100%. The scores of each ST dimension indicates the skill/preference toward that dimension. In other words, if a respondent has a score of 83.3% in complexity dimension, s/he is more comfortable working with multidimensional problems and limited system understanding than a respondent with a score of 16.7% in the same dimension (Table 4.1, first row, provides a definition of the *level of complexity* dimension). The descriptive statistics for the observed dependent and independent variables are presented in Table 4.4.

$$\text{Level of } \textit{Complexity} = (\text{Sum of more systemic answers}/6)*100 \tag{4.1}$$

Table 4.4 Descriptive Statistics for the Observed Dependent and Independent Variables.

Variable Type	Dimension	Engineering Managers (percentage)	Systems Engineers (percentage)
		Mean (*SD*)	Mean (*SD*)
Latent Dependent Variable (ST Skills Preferences)	Interaction	60.6 (27.5)	61.2 (27.1)
	Independence	48.5 (24.8)	49.6 (28.0)
	Change	50.2 (18.8)	48.7 (20.3)
	Uncertainty	40.2 (22.3)	30.8 (23.1)
	Complexity	57.2 (24.6)	55.8 (25.4)
	Sys. Worldview	47.5 (28.5)	50.0 (27.6)
	Flexibility	57.6 (27.7)	55.0 (31.6)
Latent Independent Variable (Personality Traits)	Extraversion (E)	49.3 (28.7)	53.9 (25.9)
	Intuition (N)	30.7 (22.8)	28.7 (22.1)
	Feeling (F)	41.2 (26.6)	36.5 (23.4)
	Perceiving (P)	22.6 (18.6)	23.0 (19.7)

4.5.2.2 Latent Independent Variable

To assess practitioners' "Personality Traits (PTs)," the study utilized the MBTI instrument with its four dimensions 1) level of *Extraversion* (E), 2) level of *Intuition* (N), 3) level of *Feeling* (F), and 4) level of *Perceiving* (P). These four dimensions, which are condensed into one latent variable called "Personality Traits (PTs)," are used as a personality indicator for the study's population.

The same scoring (ST scoring) system is performed to find the score for each of the four MBTI dimensions, see Equation(4.2). The three MBTI dimensions, *Intuition-Sensing, Feeling-Thinking, and Perceiving-Judging* have 20 binary questions each, and *Extraversion-Introversion* dimension has ten binary questions. The binary MBTI questions are coded in a way to make aggregate accuracy score for each dimension (for example, more *Intuitive* answer coded one while more *Sensing* answer coded zero in *Intuition-Sensing* dimension). Then, the aggregate score was converted to a percentage score. Since the score in each MBTI dimension is a continuum, each dimension was named as one extreme for simplification. As an example, the score of the *Intuition-Sensing* dimension is named "level of *Intuition,*" which contains information of both extremes of *Intuition* and *Sensing*. For instance, an individual with a 75% score in the *Intuition* dimension (which is equal to a score of 25% in *Sensing* dimension) indicates that he has a more intuitive preference than sensing preference. Therefore, an aggregate score in each of the four MBTI dimensions (ranging from 0% to 100%) is given to each respondent.

$$\text{Level of } \textit{Intuition} = (\text{Sum of intuitive answers}/20)*100 \tag{4.2}$$

4.5.2.3 Moderator Variables

Three moderator variables were utilized to investigate their interactional effects on the relationship between practitioners' PTs and the level of ST skills preferences. It was hypothesized that these three moderator variables might magnify or weaken *the relationship that exists between practitioners' PTs and the level of ST skills preferences.* The first moderator, the education level of practitioners, was coded 1 through 4 with one having other degrees such as high school diploma, associate degree, and some college credits, two as having a bachelor degree, three having a master's degree, and four having a doctorate level of education. The higher value of the first moderator represents practitioners with a higher level of education. The second moderator, the current occupation type of practitioners, was a binary variable and coded as one for engineering managers and zero for systems engineers. The higher value of the second moderator toward one represents practitioners with engineering managerial occupations and the lower value toward zero represents practitioners with systems engineering positions. The third moderator, practitioners' managerial experience, was evaluated based on the number of years a manager had been in a managerial position throughout his/her career. The managerial experience was an ordinal observed variable distinguished by five categories including five years and below (coded 1), six to 10 years (coded 2), 11 to 15 years (coded 3), 16 to 20 years (coded 4), and 21 years and above of managerial experience (coded 5). The higher value of the third moderator indicates practitioners with more managerial experience.

4.5.2.4 Control Variable

Work experience was chosen as a control variable for the third moderator variable (that is, managerial experience). The work experience was evaluated based on the number of years a manager had been in the current occupation. We were interested in investigating the moderation effect of practitioners' managerial experience, with the exclusion of their work experience, on the relationship between their PTs and ST skills preferences. Work experience was an ordinal observed variable which was distinguished by five categories (same as managerial experience categories) including five years and below of work experience (coded1), six to ten years (coded 2), 11 to 15 years (coded 3), 16 to 20 years (coded 4), and 21 years and above (coded 5).

As shown in the "*Hypotheses Development and the Proposed Theoretical Model*" section, there is much research that used demographic variables such as educational level, occupation type, managerial experience, and work experience in the context of both ST and PTs literatures. For instance, a study showed that there are some relationships between the ST skills of managers and their amount of experience (Nagahi et al., 2019). Additionally, Furnham and Stringfield (1993) reported a relationship between the managerial experience of managers and their PTs. Since there are studies in each of ST and PTs literatures suggesting managerial experience can be an impacting factor of ST and also PTs, we assumed managerial experience might influence the main relationship of the current study, which is the relationship between practitioners' ST and Pts. The same assumptions have been made for education level, occupation type, and work experience. In other words, we found these demographic variables influential in both ST and personality literatures, which potentially moderate the relationship between practitioners' ST skills and PTs.

4.5.3 Limitation

The managerial and work experience variables might be subjective due to their definitions, and consequently, the results associated with (H_4) should be interpreted cautiously; and for future research, it is beneficial to add the managers' level in the organization (e.g., CEO, middle manager and so on) as a moderator variable. Therefore, a new hypothesis can be written as practitioners' managerial level in the organization (e.g., CEO, middle manager, and so on) strengthens/weakens the relationship between personality traits (PTs) and their ST skills preferences. In addition to the current study variables, more comprehensive research might be needed to identify and utilize other control and impacting variables such as the level and position of managers in the organization related to ST skills preferences and PTs in the domain of complex systems. Other potential demographic variables such as gender, race, age, and others can be added to the proposed theoretical model to investigate their hypothetical impact on the main relationship of the study. These are some limitations of the current study, which can be investigated in future studies.

4.5.4 Construct Validity of the Theoretical Model

Before interpreting the results of the study, the proposed theoretical model needs to be validated through the establishment of construct validity. As mentioned, the proposed theoretical model, which consists of different variables related to practitioners' sample including the PTs (latent independent variable), ST skills preferences (latent dependent variable), three moderators and one control variable (that is the education level, the current occupation type, the managerial experience, and work experience) shows the structural relationship among all the study's variables through the regression and measurement weights. Two confidence intervals of 99 and 95 percent associated with *p*-values of less than 0.001 and 0.05 were used to determine significance in this study.

The construct validity of the theoretical model is obtained through the investigation of model fit indices, as shown in Table 4.5. The fit indices values indicated that the proposed theoretical model obtained the construct validity and measures what it is intended to measure; consequently, it is deemed valid to test the study's hypotheses. The reliability of the theoretical model was obtained through composite reliability. Both latent variables— PTs and ST skills preferences—achieved desirable composite reliability of 0.7 in the proposed model (Bagozzi & Yi, 1988). The construct validity and composite reliability were conducted 1) to show that the proposed theoretical model was able to measure what it is intended to measure (i.e., the proposed model fits the data), 2) to show that the associated results of the model can be generalizable, and 3) to test the study hypotheses.

Table 4.5 The Construct Validity for the Proposed Theoretical model

Name of category	Name of index	Literature	Threshold	The proposed model
Absolute fit	χ^2/DF	(Hair et al., 2009)	<3.0 Good; 3.0 to 5.0 sometimes permissible	1.80 [χ^2(df) = 184.9(103)]
	RMSEA; RMSEA	(Byrne, 2010)	RMSEA < 0.08	0.063; CI [0.048, 0.077]
		(Meyers et al., 2005)	<.08 good fit; .08 to .1 moderate fit; > .1 poor fit	
	SRMR	(Hair et al. , 2009)	SRMR<0.09 is	0.072
Incremental fit	CFI	(Bentler, 1990), (Hatcher, 1994)	CFI > 0.90	0.97
	IFI	(Meyers et al., 2005)	IFI > 0.90	0.97
Parsimonious fit	PNFI	(Meyers et al., 2005)	PNFI > 0.5	0.62

4.6 Hypotheses Testing and Results

To test the study hypotheses, the proposed theoretical model was tested through structural equation modeling using AMOS software version 24.0. The standardized solution for the theoretical model consists of the full structural model and is used to assess all the relationships among the study's variables (see Table 4.4).

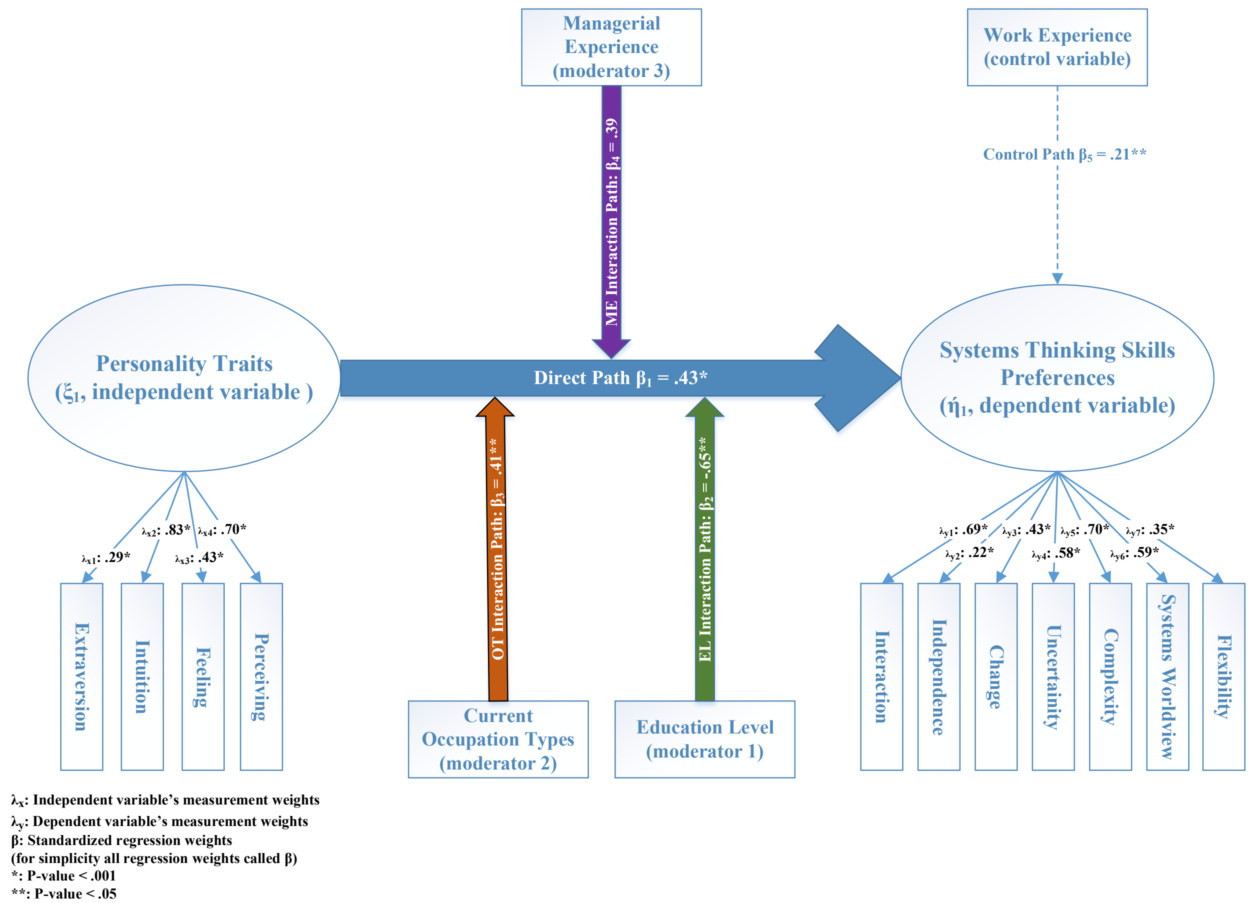

Figure 4.4 The Full Structural Model Analysis of the Proposed Theoretical Model

4.6.1 The Main Relationship Test (H_1)

As seen in Table 4.4, practitioners with high scores on the PTs dimensions of *Extraversion* (E), Intuition (N), *Feeling* (F), and *Perceiving* (P) also have high scores in the 7-dimensions of ST skills preferences namely, levels of *Complexity*, *Independence*, *Interaction*, *Change*, *Uncertainty*, *Systems Worldview*, and *Flexibility*. For example, a practitioner with a high score in the *Intuition* dimension indicates his/her clear preference toward *Intuition* compared to *Sensing*, and a practitioner with a high score in the *Complexity* dimension indicates his/her clear skill preference toward *Complexity* compared to *Simplicity* (see Table 4.4). The Practitioners with low scores on the PTs dimensions are associated with low scores on the 7-dimensions of ST skills preferences.

Since the *Interaction, Uncertainty, Complexity*, and *Systems worldview* dimensions explain most of the variance in the ST skills preferences latent variable. These four dimensions are considered to be the most critical dimensions in measuring the overall systemic skills preferences of practitioners. Similarly, *Intuition* (I) and *Perception* (P) have the highest factor loading in measuring the independent variable, PTs. In other words, practitioners with high *Intuition* and *Perceiving* characteristics have a high tendency toward working in systems that are more interactional, uncertain, large scale, and complex. This finding is consistent with other studies such as Linder and Frakes' study (2011), which showed intuitive and perceiving respondents inclined to engage in systems thinking practices. Additionally, Krumwiede and Lavelle, (2000) which showed that *Intuition* is the MBTI dimension most applicable in explaining the performance of successful total quality managers.

Since the relationship between the PTs and the ST skills preferences latent variables is significant with p-value < 0.001 (t-value = 4.75) and standardized regression weight of $\beta_1 = +0.43$ (with the standard error of 0.09), H_1 of the study is supported. This indicates that the PTs of practitioners have a positive relationship with their ST skills preferences. In other words, practitioners' PTs affect their ST skills preferences in solving complex system problems.

4.6.2 Moderation Test (H_2, H_3, and H_4)

The moderation tests were performed to explain "how" the primary relationship between the independent and dependent variables exists. To test moderation in the proposed theoretical model, the Bootstrap method is performed (Bollen & Stine, 1990; Shrout & Bolger, 2002). The Bootstrap (resampling) technique was used to ensure that the assumption of normality is maintained in the proposed model. The Bootstrap was placed on 5000 samples with a 95 percent bias-corrected confidence interval. All p values are < .05 unless otherwise noted.

As mentioned in the study variables section, three moderation variables are utilized to test their interaction effects on the relationship between practitioners' PTs and ST skills preferences. The three moderation variables are the education level, the current occupation type, and the managerial experience of practitioners. The moderation tests are conducted and interpreted according to the guidance provided in the literature, specifically the studies from Aiken and West (1991) and Dawson (2014). The standardized regression weights are used to plot and interpret the interactional effects. In other words, the independent and dependent variables have a mean of zero and *SD* of one in all interaction plots. As a result, +1 *SD* of ST skills preferences indicates that individuals have more systemic preferences than -1 *SD* of ST skills preferences. Similarly, +1*SD* of PTs indicates individuals with *Intuition* and *Perceiving* characteristics, while *-1SD* of PTs shows individuals with *Sensing* and *Judging* characteristics.

The interaction effect of the first moderator, the practitioners' education levels, was tested to determine the relationship between PTs and ST skills preferences (H_2). The interaction effect with β_2 = -0.65 was found to be significant (t-value = -2.41 and p-value = .016), indicating the presence of a moderation. Therefore, the second hypothesis (H_2) was supported. This result indicates that *practitioners' education levels weaken the positive relationship between PTs and ST skills preferences.* Figure 4.5 shows the first moderator interactions plotted at +/- 1 *SD* of ST skills preferences level (that is, practitioners with more or less systemic preferences).

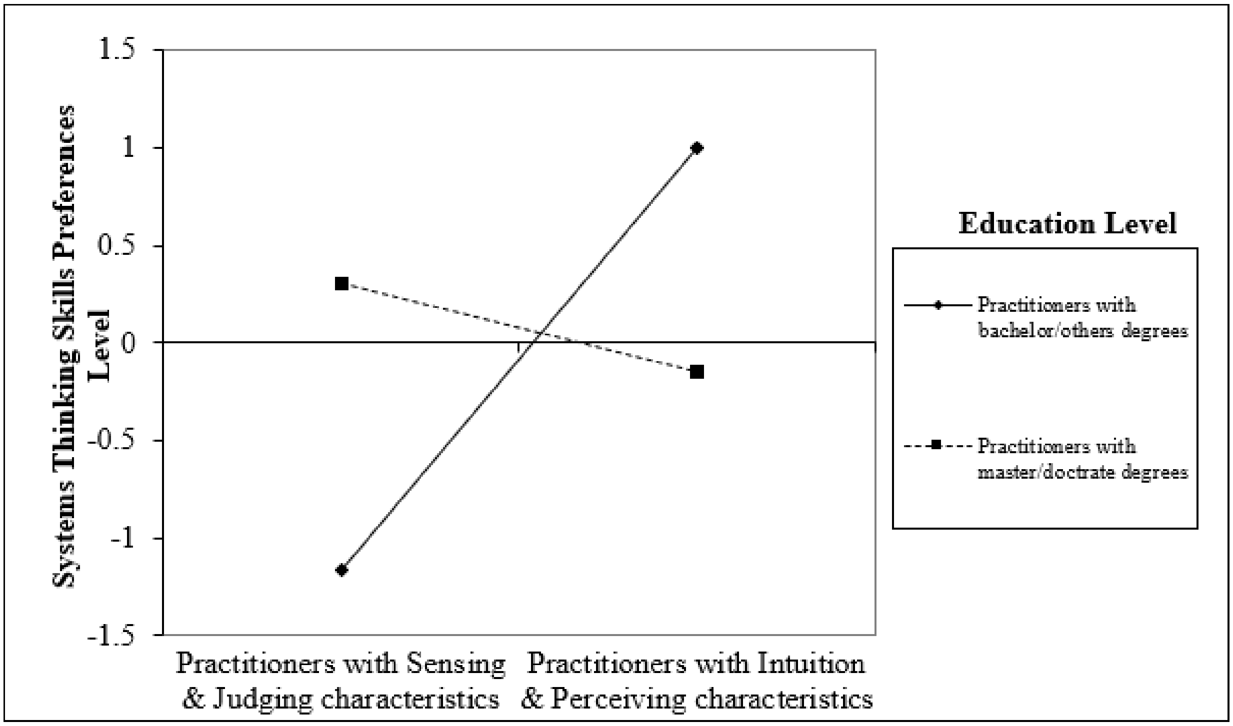

Figure 4.5 The Interaction Effect of Practitioners' Education Level as a Moderator on the Relationship between PTs and ST Skills Preferences

The interaction effect of the second moderator, the practitioners' current occupation type, was tested to determine the relationship between PTs and ST skills preferences. Results indicated a significant interaction effect of practitioners' PTs on their ST skills preferences for the second moderator, $\beta_3 = 0.41$ (t-value = 2.06 and p-value = .040). As a result, the third hypothesis (H_3) of the study was supported. *Practitioners' current occupation type strengthens the positive relationship between PTs and ST skills preferences.* Figure 4.6 shows the second moderator interactions plotted at +/- 1 *SD* of the ST skills preferences level.

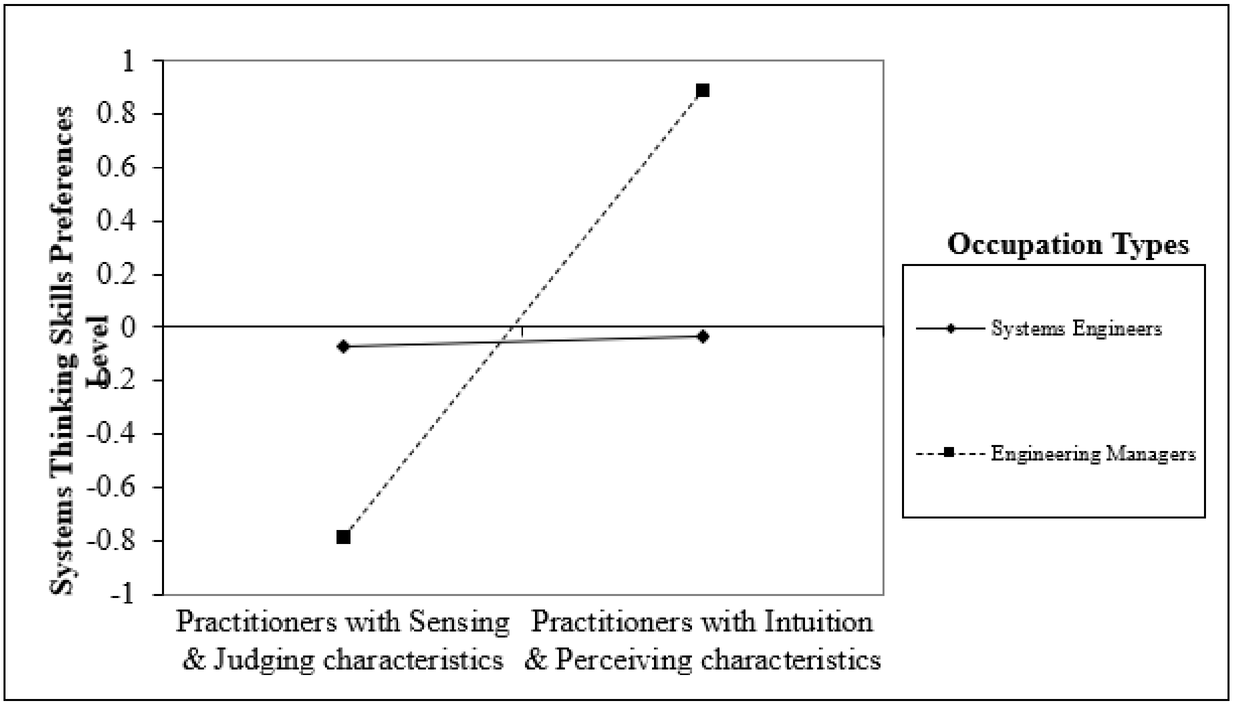

Figure 4.6 The Interaction Effect of Practitioners' Current Occupation Type as a Moderator on the Relationship between PPs and ST Skills Preferences

It was hypothesized (H_4) that practitioners' managerial experience, controlled by their work experience, moderates the relationship between PTs and ST skills preferences. The interaction effect of the managerial experience was not significant at a 95 percent confidence interval ($\beta_4 = 0.39$, t-value = 1.57, and p-value = .117), and therefore, the fourth hypothesis of this study was not supported. Although we know the interaction effect of managerial experience on the relationship between PTs and ST skills preferences is not significant, based on a study by Brambor, Clark, and Golder (2006), we interpreted the result of this interaction and suggested that there may be a "weak moderation effect." *Practitioners' managerial experiences strengthen the positive relationship between PTs and ST skills preferences.* Figure 4.7 presents the third moderator (that is, managerial experience) interactions plotted at +/- 1 *SD* of ST skills preferences level.

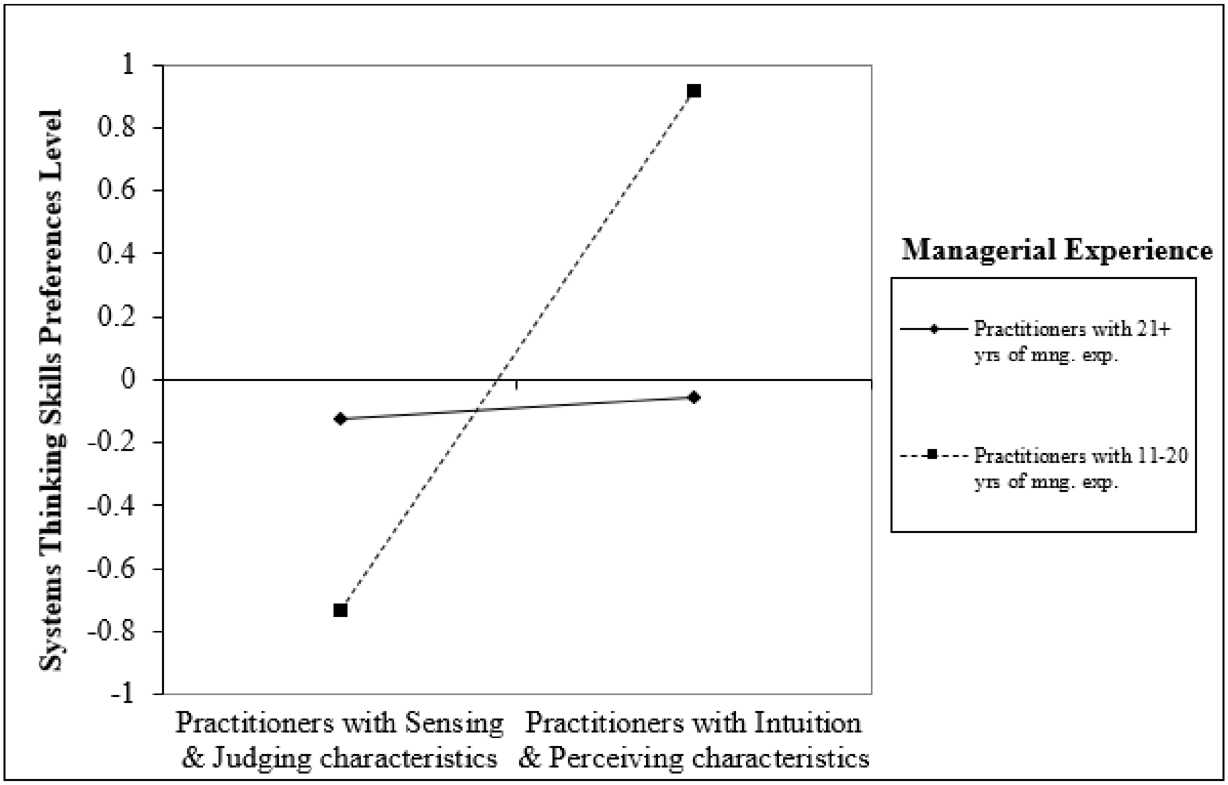

Figure 4.7 The Interaction Effect of Practitioners' Managerial Experience as a Moderator on the Relationship between PTs and ST Skills Preferences

4.7 Discussion and Implications for the Engineering Management Domain

This discussion is based on an analysis of the testing of the four hypotheses.

Contribution and validity of H_1: Based on testing, the first hypothesis was supported. Numerous studies have shown that systems thinking promotes better management of problems in the complex systems' domain (Checkland, 1999; Flood & Carson, 2013; Keating et al., 2003; Steward, 1981). In the literature, no studies are investigating the impact of systems engineers and engineering managers' PTs on ST skills preferences when education level, current occupation type, and managerial experience are added as moderator variables. Understanding the connection between PTs and ST skills preferences can help engineering managers and systems engineers match the practitioners' skills preferences with the requirements of the work environment. The contribution of the first hypothesis is consistent with other studies such as Linder and Frakes (2011), which showed there is a correlation between respondents' PTs and their preferences for using systems thinking practices. Balkis and Isiker (2005) who found a close positive relationship between different thinking styles and the personalities of university students. Davidz and Nightingale (2008) also showed that participants' personality characteristics positively affect the development of systemic thinking.

Implications of H_1 for academics and practitioners: The positive relationship between PTs and ST skills preferences indicates that engineering managers and systems engineers who scored toward high-level of *Intuition* and *Perceiving* personality traits scored toward the *Complexity*, *Interaction*, *Uncertainty*, and *Systems worldview* dimensions. This implies that perceiving and intuitive engineering managers and systems engineers are more comfortable in dealing with complex systems problems where complexity, uncertainty, and interaction are the main characteristics. This result is consistent with Linder and Frakes's (2011) study that found intuitive and (to a lesser extent) perceiving respondents have more tendency toward systems thinking practices than respondents with other PTs.

Based on the structural model analysis for this study sample, *Complexity* ($\lambda_{y5} = 0.70$), *Interaction* ($\lambda_{y1} = 0.69$), *Systems Worldview* ($\lambda_{y6} = 0.59$), and *Uncertainty* ($\lambda_{y4} = 0.58$) are the ST dimensions most correlated with the *Intuition* ($\lambda_{x2} = 0.83$) and *Perceiving* ($\lambda_{x4} = 0.70$) PTs. The main implications drawn from the results are that perceiving and intuitive engineering managers or systems engineers 1) are more comfortable working in multidimensional problems, 2) tend to accept working solutions (good enough) instead of optimal solutions, 3) enjoy working on problems that have not only technological issues but also inherent human/social, organizational/managerial, and political/policy dimensions, 4) prefer to work on solving problems within a team, 5) are less interested in identifying cause-effect paradigms, and 6) focus more on the whole system in solving problems and formulate a problem by looking at the big picture to understand the overall interaction. Based on H_1, we conclude that practitioners with *Intuition* and *Perceiving* PTs tend to be more systemic.

It is important to clarify that the ST skills preferences cannot be treated and classified as the same category as personality traits. There is a difference between skill and trait. Personality is a trait-based variable, which is a relatively stable and enduring individual difference in personality. On the other hand, ST is a more skill-based variable, which is an individual difference in specific patterns of activity during work striving and can be taught and manipulated easier than a trait. According to the interactionist perspective, skills are affected by traits and task/environment conditions (Kanfer and Heggestad, 1997). It means you can earn better systemic skills if you work on it. On the other hand, it might not be possible that a skill-based variable such as ST skill preferences influence a trait-based variable like personality traits.

Contribution and validity of H_2: Based on the research analysis, H_2 is supported. The education level of practitioners moderates the relationship between their PTs and ST skills preferences. The first moderation test showed that engineering managers and systems engineers who hold a bachelor or other degrees and have more tendency toward *Intuition* and *Perceiving* characteristics lean more toward systemic paradigms than practitioners with *Sensing* and *Judging* traits and the same level of education (Figure 4.5). Practitioners who hold graduate degrees and have more tendency toward *Intuition* and *Perceiving* traits tend to be less systemic than those who hold a graduate degree and have *Sensing* and *Judging* traits.

Implications of H_2 for academics and practitioners: The level of systems skills preferences among practitioners with bachelor/other degrees are highly sensitive to their personality traits; i.e., Intuitive and Perceiving practitioners with bachelor/other degrees are much more likely to be systemic thinkers than Sensing and Judging practitioners with bachelor/other degrees. Additionally, the level of system skills preferences found among practitioners who have graduate degrees is less sensitive to their personality traits.

Contribution and validity of H_3: According to the analysis, H_3 is also supported. The current occupation type of practitioners serves as a moderator for the relationship between their PTs and ST skills preferences. The second moderation test showed that the levels of engineering managers' ST skills preferences are sensitive to their personality traits. On the other hand, the levels of systems engineers' ST skills preferences are less sensitive to their PTs (see Figure 4.6). Results showed that engineering managers with a tendency more towards *Intuition* and *Perceiving* characteristics lean toward holistic paradigms than engineering managers who have more preferences toward *Sensing* and *Judging* characteristics. A range of studies found that the thought process, leadership, and performance of engineering managers differ depending on the manager's PTs (Cable & Judge, 2003; Tetlock et al., 1993; Williams, 2004; Zhao & Seibert, 2006).

Implications of H_3 for academics and practitioners: The main implication for practitioners is that with the presence of the second moderation, the systems engineers' PTs, have little impact on their level of ST skills preferences, but it is not the case for engineering managers. This means that engineering managers with Intuitive and Perceiving traits are potentially more comfortable working in systems that are complex and large. Sensing and Judging engineering managers prefer to work with simple small-scale complex systems problems.

Contribution and validity of H_4: Based on the analysis, H_4 is not supported. Although practitioners' managerial experience may play an insignificant role in the relationship between PTs and ST skills preferences, the associated results were interpreted as having a "weak moderation effect." For more details about the "weak moderation effect," readers can refer to the work of Brambor et al. (2006).

The result of the last moderation test found that a practitioner with 11-20 years of managerial experience and a preference toward *Intuition* and *Perceiving* traits is much more inclined toward systemic paradigms than a practitioner with similar experience and a *Sensing* and *Judging* PTs. This is consistent with Porter (2008), who stated that managerial experience affects the level of managers' systems skills capabilities concerning corporate social responsibility issues. Additionally, Nagahi et al. (2019) showed that managers with more experience possess relatively more ST skills than their counterparts. Bureš and Čech (2007) also emphasized the effect of managerial experience on teaching and understanding systems thinking concepts.

4.7.1 Implications for the Education and Policy Domains

Quenk (2009) defines intuitive individuals as concentrating more on perceiving patterns and interrelationships. Intuitive individuals have five dominant characteristics including 1) focus on the abstract meaning of ideas, 2) imaginative in engaging in a new experience and solving problems, 3) enjoy conceptual knowledge and complexity, 4) trust theoretical patterns and interrelationships, and 5) value originality and uniqueness (Quenk, 2009). Quenk (2009) also describes perceiving people as inclined toward flexibility resulted in dealing with the outer world. Perceiving people have five major features: 1) flexible approach in dealing with both the expected and unexpected events as occurring, 2) prefer flexible plans and freedom to choose, 3) gather ideas and materials following specific deadlines, 4) unmotivated by routines, and 5) comfortable dealing with emergent behavior regardless of detailed plans.

Our finding is consistent with Quenk's study, where the Level of *Complexity*, level of *Interaction*, level of *Systems Worldview*, and level of *Uncertainty* are highly correlated with the *Intuition* and *Perceiving* dimensions of PTs. This would inform practitioners that individuals with a more intuitive and perceiving personality have more systemic skills. Consequently, practitioners can train individuals to become more systems thinkers by focusing on the mentioned personality features in the *Intuition and Perceiving* dimension. These features are permissible to train students in the K-12 education system, and work-training environment to enhance the possibility of equipping the current, future systems engineers and engineering managers with a high level of systemic thinking. Identifying the connection between PTs and ST skills can provide direct utility for practitioners and enhance the system's performance by fitting individuals' skillset and personality with their job requirements in a timely fashion. This would reduce the burden of long training costs and prepare companies to provide the relevant needed training for their employees based on their skillset and personality types.

Additionally, the improvement of ST skills and certain personality traits can be supported through engineering curriculums across colleges, and determine which majors produce more systems thinker students than others. In order to improve these skills, the curriculum should be revised to design more courses that are relevant to solving complex system problems (Assaraf & Orion, 2005; Frank, 2001; Sweeny & Sterman, 2000). This will enhance critical thinking power and provide new viewpoints and ways of thinking to understand and solve complex system problems. Redesigning the educational curriculum in such a way would foster students' formation of holistic thinking along with their personality traits. Moreover, identifying more systemic thinking based on personality profiles can help students in understanding the influence of the level of ST and personality traits with respect to taking actions and making decisions in complex system problem domains.

If complex system problems cannot be solved using traditional engineering methods, then there is a need to use more systemic approaches. Research shows that socio-technical system problems require more systems thinkers since these problems contain technical, culture, policy, and social components (Boardman & Sauser, 2006; DeLaurentis, 2005; Jaradat et al., 2018). Managing and engineering socio-technical systems require a cadre of individuals who are capable of taking a more holistic approach. Examples of these approaches include *big picture analysis*, *understanding the interrelationships of a robust casual chain of the events*, *consideration of integration within system of systems*, and *chaos management*.

Big picture analysis would enable systems engineers and engineering managers to better understand the whole aspect of a complex system problem. The focus on much detail might hinder the process of achieving acceptable solutions, and it is more likely to yield to type III errors—solving the wrong problems precisely (Mitroff, 1998).

Understanding the interrelationships of a robust casual chain of the events is necessary for systems engineers and engineering managers because a simple linear cause-effect paradigm is not sufficient to understand the connectivity and interaction of large-scale complex system problems. It is not feasible to achieve a full understanding of complex systems using the simple one-cause one-effect approach. The ST-based paradigm is much more consistent with the working environment of systems engineers and engineering managers.

Consideration of integration within system of systems allows practitioners to not only plan based on the requirements of the individual systems, such as different sections and departments within an organization, but also consider the requirements of the organization as the whole unit. This creates better management and planning for a system of systems based on holistic systemic approaches.

Chaos management equips systems engineers and engineering managers against the emergent behavior of complex systems, especially in the phase of operations. Such emergent behaviors are unintended and problematic, which exposes the entire system in a higher degree of risk and danger. Consequently, systems engineers and engineering managers should have more flexible and resilient plans to adapt to these unpredictable and unexpected problems of complex systems. A holistic systemic approach can help practitioners to more effectively deal with the unintended and unpredictable challenges of complex systems domain.

The ST skills preferences profiles generated using the ST skills instrument are not meant to place judgment on a practitioner's capabilities. In other words, there are no good or bad profiles, and both holistic and reductionist thinkers might be needed in the work environment. Depending on the specific scenario and environment, more systemic thinkers may be appropriate (such as managerial positions), while in other situations (such as specific engineering or data analytic positions), reductionist thinkers may be more suitable to handle the challenges. For a better work environment, it is better to match the level of ST skills/preferences of individuals with their level of environmental complexity.

4.7.2 Future Studies

There is a lack of studies that investigates the relationship between practitioners' personality traits and the level of ST in the field of systems engineering. As a result, future studies are needed to test the consistency and generalizability of the findings of the current study with the findings of future similar studies. Since the sample of this study was limited to engineering managers and systems engineers, other samples from different populations of interest, including non-engineering managers and non-system engineers, can be investigated in future studies to test the effects of PTs on ST skills preferences across different categories. Data from that study could then be used in another study comparing the results of different sample studies.

Although the "MBTI instrument" adopted by Keirsey and Bates (1984) is used as the PTs indicator in the current study, the Five-Factor Model (FFM) is another widely used personality indication tool popular in academic research (Furnham, 1996). Future studies could use the NEO-PI Five-Factor Model (FFM) and proactive personality instruments as the PTs predictor, and their results could be compared with the results of this study, which used the "MBTI instrument." Classification of the proposed model with respect to PTs and ST skills preferences classes (both PTs and ST skills preferences are latent variables) using Bayesian latent class analysis (BLCA) can be performed in future studies. Moreover, we should emphasize that we found evidence of construct validity for the proposed theoretical model of this study, which means our proposed model can measure what it was intended to measure; however, for the final construct validation of a theoretical model, more studies are needed to test the validity and reliability of the proposed model with different populations of interest during different periods of time.

In this study, the instrument data was used as a quantitative approach. However, according to Cresswell and Cresswell (2018), in addition to the close-ended survey, several data collection strategies can be used to analyze data including, census data, interviews (for example, researching about feeling, experience, or behaviors of LGBTQ students' peers in the classroom), observations, documents, records, observational checklists (researching about academic/instructional behaviors of students in the classroom), and other methods. These data collection strategies can be used, in future studies, as supporting methods to provide more insights about the study findings. Finally, no causality should be inferred from the study results.

In our long-term ST research, a methodology called ST-Cap Method has been designed and utilized. The ST-Cap Method is exemplary of an ST approach that guides identification, assessment, and development of ST for individuals and organizations. The ST-Cap Method is conducted in six steps. The primary goal is to determine the degree of ST that exists in an organization and the congruence of that capability to that which is demanded. For example, in a job with routine, linear, technical, and focused scoped condition, a reductionist practitioner might be needed rather than a holistic thinker. For clarification, the mentioned sentence is modified in the revised version. The long-term ST research (ST-CAP method) will:

(1) Assess individuals' level of systems thinking skills across different domains,
(2) Assess the level of environmental complexity of an organization,
(3) Match between individuals' systems thinking skills/preferences and environmental complexity,
(4) Assess the actual behavior based on the systems thinking skills,
(5) Investigate if there is a relationship between individuals' ST skills/preferences and the actual ST performance,
(6) Identify the gaps between an individual's ST skills and employers' ST needs.
(7) Suggest changes in policy, education, curriculum, and others based on the gap analysis

The current research, presented in this paper, mainly related to the first step of the long-term ST research. Moreover, the other steps are conducting or will be conducting in future studies.

4.8 Reference

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CHAPTER V

CLASSIFICATION OF INDIVIDUAL MANAGERS' SYSTEMS THINKING SKILLS BASED ON DIFFERENT ORGANIZATIONAL OWNERSHIP STRUCTURES

Nagahi, M., Hossain, N. U. I., Jaradat, R., Dayarathna, V., Keating, C., Goerger, S., & Hamilton, M. (2020). Classification of individual managers' systems thinking skills based on different organizational ownership structures. *Systems Research and Behavioral Science*. https://doi.org/10.1002/sres.2767

5.1 Abstract

The complexity resulting from an organizational structure hinders the organizational value creation capacity by challenging the decision-makers to properly allocate the strategic resources and to successfully implement viable strategic planning. To deal with these challenges effectively, organizational managers require a systems thinking (ST) approach to understand the interaction and interdependencies among the various sub-elements of the organizational structure. The current body of literature lacks studies related to organizational managers' classification of systems thinking (ST) skills based on both their overall systemic tendency and the organizational ownership structure. The purpose of this study is to assess and classify the ST skills of senior managers who currently work in a complex business environment. Initially, we clustered managers' Overall Systemic Thinking (OST) using the Bayesian Latent Class Analysis (BLCA) method into two distinct clusters: *managers with upper OST (i.e., holistic thinker)* and *managers* *with lower OST (i.e., reductionist thinker).* Further, we classified managers' ST skills into two predefined classes (public and private) to understand the characteristics of each group better. Comparative analyses and post-hoc tests were performed to test the research hypotheses. A total of 51 senior managers from two different organizational structures—public and private—participated in this study. The findings of the research show that the ST skills of managers in public are more toward the upper OST/holistic cluster, whereas managers from the private sector have an inclination toward lower OST/reductionist cluster.

Keywords: *Systems thinking, systems thinking skills, system of systems, complex systems, public and private sector, senior managers, classification, clustering, Bayesian Latent Class Analysis (BLCA).*

5.2 Introduction

Business organizations are characterized by internal factors such as resources, structures, and cultures as well as external factors such as economic, social, legal, and political. The literature identifies several characteristics for complex systems, and in this study, we adopt the characteristics derived from Jaradat and Vemuri's studies where uncertainty, emergence, ambiguity, and evolutionary development are main characteristics of complex systems (Jaradat, 2015; Jaradat and Keating, 2016; Jaradat, Keating, and Bradley, 2018; Vemuri, 2014). These characteristics are central in delineating internal and external factors of organizations.. It is from this vantage point that business organizations are classified and treated as complex systems for this study.

Change management, with a focus on maintaining proper coordination among the different sub-elements of a business organization, is a primary challenge for managers. This is due in large part to the interrelated nature of internal and external factors as organizations operate as complex systems. To lessen the negative impact of these challenges and better manage complex system problems, decision-makers should be equipped with the necessary skillset and knowledge needed to understand interactions of different dimensions (e.g., culture, social, and political) in their business network. There is a necessity to apply a more "systemic" holistic approach that exists in a higher Systems Thinking (ST) level (Checkland, 1999; Hossain and Jaradat, 2017; Nagahi et al., 2019). ST enhances a manager's ability to understand and manage complex factors, system elements, and interactions across different organizational structures.

In terms of employer type/business ownership structure, organizations can be separated into two segments: *public and private* (Rainey et al. 1976; Boyne, 2002). Generally, public organizations are owned by the government and federal agencies and are funded by tax revenue, whereas private organizations are owned by a collection of shareholders. Unlike private organizations, public organizations are governed by political forces rather than market forces. Public-sector organizations are subject to bureaucratic checks and balances, laws, and regulations, but private sector organizations set their own goals and have more freedom to operate (Boyne, 2002). The different types of organizational structure based on the ownership structure might suggest managers with a different and perhaps specific set of ST skills. In other words, public managers might have different ST skills compared to private managers. Nevertheless, for both structures, complex problems continue to confound the capability of organizational managers. Thus, there is a need to develop a cadre of effective organizational managers, capable of efficiently addressing complex systems problems across a spectrum of organizations and circumstances. However, there is no robust evaluation criteria exist to assess managers' ST skills. In response, this study is structured to pursue three fundamental purposes: (i) to assess managers' overall systemic thinking skills when dealing with complex systems, (ii) to classify their ST skills based on the organizational ownership structure to which they are assigned, and (iii) to compare the results of clustering and classification techniques to better understand the ST characteristics of public versus private sector managers.

5.3 Research Background and Motivation

Active ST research has existed for over two decades and is considered one of the essential topics in management studies. One of the earliest discussions of systems thinking as applied to an organizational system first appeared in a 1986 by Gareth Morgan, who provided a biological metaphor to describe how an organization works. This metaphor shows that both organizations and biological organisms constantly exchange information with their environments and interact such that they maintain harmony with their internal and external environments through information flow and feedback.

Employing a higher level of thinking like that embodied in ST allows for a more critical examination of the interdependencies among different entities in an organization and implements better coordination among the sub-elements within the organizational structure (Palaima and Skaržauskiene, 2010). ST approaches – which include dynamic thinking, mediated modeling, mental modeling, and structural thinking – promote understanding of behavior from technical, human, and organizational levels (van den Belt et al., 2010; Jaradat, 2015). This more comprehensive understanding of behavior fosters a better decision-making process for business managers (Palaima and Skaržauskiene, 2010; Long, 2013). With the information derived from applying ST, it is possible to maintain a better balance between the degree of autonomy (choice of the decision) and integration (bringing together) of an organizational structure (Reason, 2007). ST also helps to provide conceptual grounding and enables organizational managers to develop a mental map of a particular problem.

Several existing studies have attempted to formalize the concept of ST with the term "managerial cognition" by stating that ST concerns such as "mental maps," "meta-learning," "structural thinking," "cognitive belief," and mindset are all embodied in the concept of managerial cognition (Walsh and Fahey, 1986; Calori et al., 1994). Another stream of research showed that the three classes of competencies – namely, cognitive, emotional intelligence, and social intelligence – could impact managerial cognition (Spencer and Spencer, 1993; Hopkins and Bilimoria, 2008; Dreyfus, 2008; Palaima and Skaržauskienė, 2010, Boyatzis, 2011). These streams of research also stress that ST belongs to cognitive competency. The general interpretation of this research stream is that top-level managers are often considered to be "cognizers" and require a higher level of cognitive competency in order to solve complex problems. These complex problems may include issues such as organizational performance, mapping methodologies, subjective forecasting, organizational configuration, design innovation, product development, and rational choice under a given circumstance to name a few. Because the context of complex problems across different organizational structures (i.e., public and private) may vary, the nature of the organizational structure might influence managers' cognitive mapping capability and determine their personal preference toward a decision-making process. Therefore, managers' systems skills and cognitive capability across different organizational structures might differ from one another. Cats-Baril and Thompson (1995), Boyne (2002), Gomes et al., (2012), Kwak et al., (2014), PMI (2014), and Gasik (2016) have all demonstrated why the public-sector-managers' systems skills differ from those of private managers. For example, Boyne (2002) reviewed 34 empirical studies regarding the differences between public and private sectors and found that public managers are more materialistic and bureaucratic and possess weaker organizational commitment than private managers. As another example, Gasik (2016) stated public project management is more complex than private projects management because public projects are more exposed to political and external forces, higher number of stakeholders, more conflicting interests, and frequent management changes.

Another stream of research found in the literature focuses on ST's influence in enhancing the managerial decision-making process to deal with uncertainty in the organizational environment. For instance, van den Belt et al. (2010) used a mediated modeling approach to augment managerial decision-making in the public sector. He incorporated qualitative mapping and mental-modeling techniques to promote and improve the collaborative decision-making process. A study conducted by Martens (2011) showed that ST strengthens the managerial decision-making process because it helps to assess the problem structure from a holistic point of view. Similarly, Cramp and Carson (2009) and Petkov et al. (2007) used a soft systems approach for multi-criteria decision making in a complex situation. Donovan (2017) demonstrated the application of ST in practicing safety leadership decisions in a large-scale project. By the same token, Ulrich (1983, 1988) and Achterkamp and Vos (2007) applied ST to resolve the criticality pertaining to the managerial decision-making process in making a deal with stakeholders. The general insights drawn from these studies suggest that ST aids in developing the cognitive mapping of the organizational process and fosters managerial abilities to choose the optimal decision among different alternatives.

In recent years, to achieve administrative goals, the frequency of incorporating a ST approach in the enterprise system has significantly increased. For instance, Akhtar et al. (2018) analyzed how an individual's ST ability influenced the organization's overall effectiveness. Their study's results indicated that ST aids in building a mental map of the organization's functional structure that can be used to assess the principal pattern of the organizational process, which enhances organizational efficiency. Jaaron and Backhouse (2014) and Kim et al. (2014) employed the ST approach in the service organization system to improve organizational absorptive capacity and resilience. The general findings of these studies suggest that ST enables an employee to understand the dynamics of the organization. Similarly, Chandon and Nadler (2000), Skarzauskiene (2010), and Sun et al. (2014) highlighted the importance of ST as a catalyst for organizational development and quality improvements. In another research study, Maon et al. (2008) suggested the importance of ST to fulfill corporate social responsibility and achieve organizational goals.

Although several research efforts attempted to apply ST in different sectors of the organization, there is no reported study that assesses an individual's ST skills based on the business ownership structure. Main gaps in the literature, and the study response, include the following:

- Lack of studies clustering managers based on the ST skills — identifying predisposition for holistic or reductionist thinking preferences. Thus, in this study, we implemented the Overall Systemic Thinking (OST) construct, indicated by seven distinct dimensions of ST skill instrument and then clustered the managers according to the OST construct. In other words, data analysis is targeted to examine distinctions among managers related to holistic and reductionist preferences. Although many theoretical studies discuss the comparison between holistic and reductionist thinkers, to the best of our knowledge, no study has examined this claim with advanced data analysis.

- Lack of research assessing and classifying the ST skills of managers based on business ownership structure—public versus private. In this study, we examine differences between public-sector managers and private sector managers with respect to systemic skills. The focus is on examining the hypothesis that public sector managers have a higher tendency toward holistic thinking than private sector managers who are more inclined to engage in reductionist thinking.

To address these gaps, this study aims to cluster and classify the managers based on OST and business ownership structure (public and private) and then highlight the correlation between organizational ownership structure and managers' OST in the complex system.

The hypothesis development is discussed next, which is followed by the study methodology. Bayesian Latent Class Analysis (BLCA), an advanced clustering and classification technique, is used to analyze and describe the result. We then report the results in terms of a dichotomous output from the Binary Logistic Regression (BLR) method. We also test the hypotheses with Tukey HSD tests as a post-hoc multiple group comparison method. The ST profile comparison between public and private managers is presented to interpret the study results, and the article ends with conclusions, limitations, and avenues for future research.

5.4 Hypotheses Development

The complexity of public and private organizations varies in different key attributes such as management process, workers' efforts, job performance, level of efficiency, monetary incentive, and motivation (do Monte, 2017). In his book, Kettl (2011) mentioned that public organizations deal with complex problems that result from legislative processes while private sector managers engage with less complex problems as they can often define their organizational goals independently. Boyne (2002) also supported the previous idea by stating that the public sector is subject to government rules and regulations more than the private sector in the sense that private employees have more freedom to operate with greater autonomy. In order to identify the differences between private and public managers' comfort level to work in *complex* problems, H_1 is hypothesized.

H_1: Public and private managers can be classified into two different groups with respect to the level of the tendency for Complexity skill.

As shown in Table 5.1, the level of *independence* measures an individual's flexibility when making collaborative decisions and his/her aptitude to handle different elements in an organization. Public and private organizations' managers show significant differences when making decisions in terms of the quality and accuracy of the information they work with (Dillon et al., 2010). In their study, the authors also reported that public-sector decisions are influenced by political forces, thus forming a reactive and bottom-up decision structure while the private sector follows a proactive and top-down decision structure. Nutt (2005) pointed out that external interest groups can derail the public sector decision-making process moreso than the impact of internal politics on the private sector. Moreover, Maurel et al. (2014) explained that the degree of system integration in the two sectors could be different with regards to the socio-economic impact. With respect to exercising leadership, public-sector managers have less autonomy than private-sector managers (Hooijberg and Choi, 2001). Thus, we hypothesize H_2, to identify the difference in thinking behaviours of public and private managers regarding the *independence* tendency.

Table 5.1 Seven Pairs of ST in the Seven ST Dimensions (Jaradat, 2015, p.65)

Less Systemic (Reductionist)	Dimension	More Systemic (Holistic)
Simplicity (S): Avoid uncertainty, work on linear problems, prefer the best solution, and prefer small-scale problems.	***Level of Complexity***: Comfort with multidimensional problems and limited system understanding	**Complexity (C)**: Expect uncertainty, work on multidimensional problems, prefer a working solution, and explore the surrounding environment.
Autonomy (A): Preserve local autonomy, tend more to an independent decision and local performance level.	***Level of Independence***: Balance between local level autonomy versus system integration	**Integration (G)**: Preserve global integration, tend more to a dependent decision and global performance.
Isolation (N): Inclined to local interaction, follow a detailed plan, prefer to work individually, enjoy working in small systems, and interested more in cause-effect solution.	***Level of Interaction***: Interconnectedness in coordination and communication among multiple systems	**Interconnectivity (I)**: Inclined to global interactions, follow the general plan, work within a team, and interested less in identifiable cause-effect relationships
Resistance to Change (V): Prefer taking few perspectives into consideration, over specify requirements, focus more on internal forces, like short-range plans, tend to settle things, and work best in a stable environment.	***Level of Change***: Comfort with rapidly shifting systems and situations	**Tolerant of Change (Y)**: Prefer taking multiple perspectives into consideration, underspecify requirements, focus more on external forces, like long-range plans, keep options open, and work best in changing environment.
Stability (T): Prepare detailed plans beforehand, focus on the details, uncomfortable with uncertainty, believe the work environment is under control, and enjoy objectivity and technical problems.	***Level of Uncertainty***: Acceptance of unpredictable situations with limited control	**Emergence (E)**: React to situations as they occur, focus on the whole, comfortable with uncertainty, believe the work environment is difficult to control, enjoy subjectivity and non-technical problems.
Reductionism (R): Focus on particulars, prefer analyzing the parts for better performance.	***Systems Worldview***: Understanding system behavior at the whole versus part level	**Holism (H)**: Focus on the whole, interested more in the big picture, interested in concepts and abstract meaning of ideas.
Rigidity (D): Prefer not to change, like a determined plan, open to new ideas, motivated by routine.	***Level of Flexibility***: Accommodation of change or modifications in systems or approach	**Flexibility (F)**: Accommodating to change, like a flexible plan, open to new ideas, and unmotivated by routine.

H_2: Public and private managers can be classified into two different groups regarding the level of Independence tendency.

Table 4.1 defines the level of *interaction* as the way managers interact with their systems. Checkland (1999) stated that managers should have the ability to recognize and manage interactions in their organizations. A comparative study was conducted by Melin and Axelsson (2013) to explore the similarities and differences of inter-organizational interactions in private and public organizations. The findings indicated that both sectors are similar in the degree of responsiveness and leadership support but differ in their level of formality and use of technical systems when building interactions. Chen and Rainey (2014) pointed out that teamwork is an essential element for public organizations, as they need to constantly interact and share information with political parties, legislators, and interest groups. We hypothesized as follows:

H_3: Public and private managers can be classified into two different groups based on the level of Interaction tendency.

Coping with rapid changes in an organizational framework appears to be a key challenge for organizational managers. Casile and Davis-Blake (2002) explained that private organizations are excessively influenced by technical factors, while institutional factors affect public organizations when engaging with changes. Jurisch et al. (2013) emphasized that the public sector is constantly engaging with changing organizational processes to tackle social and political challenges. H_4 seeks to discover the differences between public and private managers regarding the level of *change* tendency.

H_4: Public and private managers can be classified into two different groups in terms of the Change tendency level.

The ability to work in a turbulent business environment and make decisions under pressure can be a reliable measurement for the role of a manager (see Table 5.1). Hall and Moss (1998) stated that adding a diversified workforce and better management-development process would succeed in meeting organization goals in an *uncertain* environment. The private sector exhibits lower stability than the public sector as the organizational goals are more geared toward being revenue driven and exercising limited liability (Essig and Batran, 2005). Thus, we hypothesized as follows:

H_5: Public and private managers can be categorized into two different groups regarding the level of Uncertainty tendency.

As illustrated in Table 5.1, the level of *systems worldview* tendency measures the way an individual views a problem in a complex system. Jaradat (2015) described two types of systems worldview, namely, *holism and reductionism*. In his paper, he defined *holism* as a focus on the whole system and *reductionism* as a focus on particulars. In another work, Jaradat emphasizes that organizations need both types of systems thinkers depending upon the nature of the complex problem (Jaradat et al., 2018). The sixth hypothesis (H_6) seeks to discover the public/private managers' view on complex problems.

H_6: Public and private managers can be classified into two different groups with respect to Systems Worldview tendency.

The level of *flexibility* describes an individual's preference to deal with organizational problems (Table 4.1). Hamtiaux and Houssemand (2012) identified two profiles as they relate to an individual's preference: *flexibility* and *rigidity*. While *flexibility* is the general tendency of an individual to adapt to new circumstances, *rigidity* is defined as the lack of adaptable behaviors.

The hypothesis below explores the difference between public and private sector managers' tendency toward *flexibility*.

H_7: Public and private managers can be classified into two different groups regarding the level of Flexibility tendency.

Based on the literature discussed above (e.g. Dillon et al., 2010; do Monte, 2017; Hamtiaux and Houssemand, 2012; Jaaron and Backhouse, 2011, 2014; Jaradat et al., 2018; Melin and Axelsson, 2013; O'Donovan, 2011; Zokaei, 2011), we can conclude that public managers and private managers have different tendencies with respect to seven dimensions of ST skills. *Average systems thinking* is defined as the average of all seven dimensions of ST skills. More precisely, average ST captures the manager's average ST tendency based on the seven dimensions described above. We proposed the following hypothesis to discover the differences/similarities between private- and public-sector managers in terms of their average ST skills.

H_8: Public and private managers can be classified into two different groups regarding the average ST score tendency.

5.5 Methodology

The primary goal of the study is to cluster and classify the managers based on OST and business ownership structure (public/private) and then highlight the correlation between organizational ownership structure and managers' OST in complex business environments. Figure 5.1 presents the study methodology. To test the hypotheses of the study, the methodology section is divided into three sections: 1) the introduction of the measurement scale used in this study, 2) the procedure used for data collection, and (3) the techniques applied to analyze the data and interpret the results.

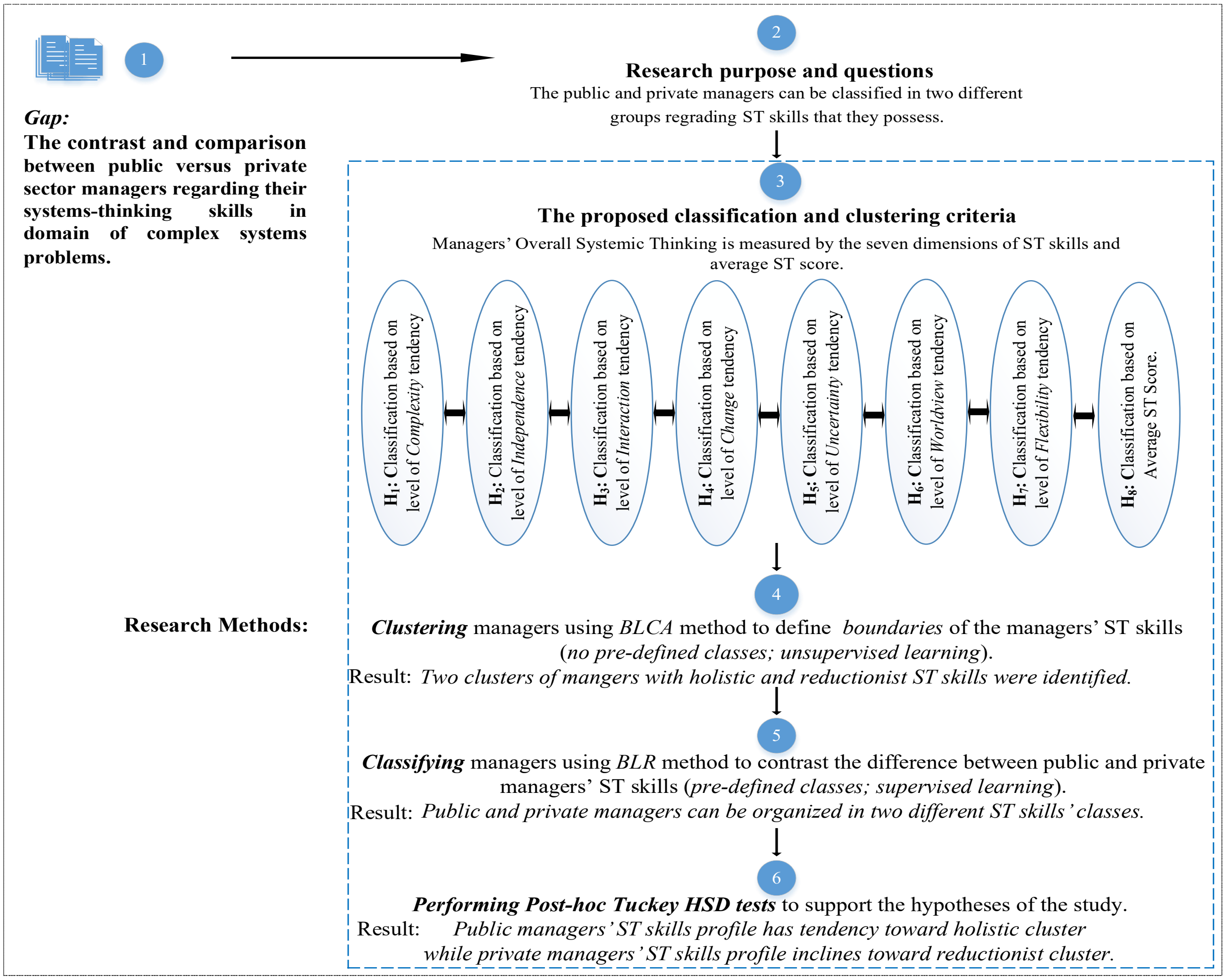

Figure 5.1 Th Fourth Study's Methodology

5.5.1 Systems Thinking Skills Instrument

In this study, we used an established instrument to measure an individual's level of ST skills in dealing with complex system problems (Jaradat, 2015; Jaradat et al., 2018). This instrument was developed by qualitative and quantitative data approach, referred to as "grounded theory." The ST skills instrument showed a very good level of reliability (α = .87), based on the recommendation of Nunnally and Bernstein (1994). More details about the instrument can be found in Jaradat (2015), Jaradat and Keating (2016), and Jaradat et al. (2018).

Thirty-nine binary questions from a web-based survey were answered by different participants. The rationale for selecting this instrument lies in its ability to comprehend all the aspects of the systemic skills necessary to solve complex systems problem efficiently. Participants chose their preferred response from each dichotomous choice (e.g., “Do you prefer to (a) organize a team to explore the problem or (b) work individually on a specific aspect of the problem”). A score sheet was used to capture an individual’s level of ST skills. The result of this instrument generates a unique profile for each respondent based on scores obtained from each dimension (Jaradat, 2015, p. 65). Each profile contains seven main letters (consistent with the distinctions of the dimensions in Table 5.1) that identify an individual’s dominant state of ST, thus determining their inclination to deal with complex system problem domains. The specific typology of this instrument is illustrated in Table 5.1 above.

5.5.2 Data Collection and Sample Size

The population of interest for this study included 51 senior managers from 12 organizations who spent a significant amount of their career in public or private sectors. Each one of the senior managers had at least 21 years of managerial experience. These top-level managers were interviewed to determine their ST skills depending on their business environment’s level of complexity. Among 51 senior managers, 18 of them have spent a significant amount of career time in the public sector, whereas 33 of them have had primarily private-sector management careers. Among 18 public managers, two of them were Ph.D. holders, 12 held master’s degrees, and 4 held bachelor’s degrees. The 33 private-sector managers included 3 Ph.D.’s, 24 master’s degrees, and

6 bachelor's degrees. A clean dataset without missing values was used to conduct the study's analysis.

5.6 Data Analysis and Results

This subsection's contents are fourfold. A statistical summary is presented first. Cluster analysis using *Bayesian Latent Class Analysis (BLCA)* was performed to define the possible clusters of ST skills in the dataset. We then classified ST skills of managers based on their employment sector —*public* or *private* using *Binary logistic regression (BLR)* to contrast each class's characteristics. The difference between clustering and classification analysis exists in the group's definition. In clustering analysis, there are no pre-defined groups, and groups will be defined based on data characteristics. On the other hand, groups are pre-defined in classification analysis, which provides some insight regarding the characteristics of pre-defined groups such as public versus private managers. Finally, we present four Tukey HSD post-hoc tests to show the difference between public and private sector managers.

Each test analyzes the data from a specific aspect. Cluster analysis, an unsupervised learning technique, shows that it is feasible to categorize managers into holistic thinkers and reductionist thinkers. Classification technique is used as a supervised learning technique to investigate whether or not public and private managers possess different systemic skills. Finally, post-hoc tests examine the study's hypotheses by comparing the results between clustering and classification analyses. *Post-hoc tests indicate that public managers are more inclined toward the holistic-thinker cluster, whereas private managers have reductionist tendencies.*

5.6.1 Summary of Statistics

After analyzing the participants' response, a profile is assigned for each respondent based on score ranges from 0 to 100 for each dimension. Finally, the average of seven dimensions' scores is calculated for every respondent. Table 5.2 shows the mean and standard deviation for seven dimensions of ST skills and the average ST score corresponding to public and private managers. Further, we found that the distributions of all observed variables met the assumptions of normality test with respect to the threshold of skewness < |2.0| and kurtosis <|7.0| (Schminder et al., 2010).

Table 5.2 The Mean ST Scores in Seven Dimensions, Average Score, and Normality Test

Managers	**Public Sector** ***N* = 18** ***M*(*SD*)**	**Private Sector** ***N* = 33** ***M*(*SD*)**	**Normality test**	
			Skewness	Kurtosis
Complexity	73.1(22.3)	49.2(22.8)	0.13	-0.89
Independence	55.6(27.9)	57.0(25.6)	-0.05	-0.54
Interaction	69.4(17.4)	63.1(24.9)	-0.56	0.17
Change	63.9(19.2)	48.0(19.9)	-0.43	0.51
Uncertainty	40.7(22.3)	26.3(19.1)	0.35	-0.56
Worldview	66.7(27.4)	54.6(28.4)	-0.02	-0.98
Flexibility	77.8(26.5)	45.5(27.1)	0.07	-1.41
Average Score	64.9(13.6)	49.1(13.2)	0.33	-0.55

*ST scores are calculated out of 100.

5.6.2 Clustering Using Bayesian Latent Class Analysis (BLCA)

Latent class analysis (LCA) is a person-centered statistical method that groups individuals into clusters based on responses that exhibit similar patterns (Liu et al., 2017). LCA is similar to typical Cluster Analysis (CA) in that both methods cluster individuals homogeneously (Porcu and Giambona, 2017). However, LCA compensates for two major drawbacks associated with CA: (1) the absence of an underlying statistical model and (2) the inability to provide a probability for an individual who belongs to a particular class (Porcu and Giambona, 2017). Cluster analysis is unsupervised learning (i.e., no predefined classes) as opposed to classification (i.e., supervised learning using pre-defined classes). We used clustering analysis utilizing BLCA as a pre-processing/intermediate step for the classification method in the next section.

In this study, overall systemic thinking (OST) is designed as a latent/unobserved dependent variable, and ST scores of the managers are considered as the actual observed variables. We measured OST through seven dimensions along with the managers' average score of ST skills, as shown in Figure 5.2. Bayesian LCA provides all feasible and validated clusters of OST based on the actual observed variables (ST skills scores of the managers). Since BLCA is used to cluster manager OST without any pre-defined groups, the spectrum of BLCA clusters will be between the cluster with the upper level (holistic) OST and the cluster with the lower level (reductionist) OST. However, manager OST can be further clustered in different segments depending on the number of clusters identified by the BLCA method. For example, if BLCA results in a 5-cluster solution, then these clusters can be segmented as holistic, middle holistic, neither holistic nor reductionist, middle reductionist, and reductionist cluster.

AMOS software version 24.0 was used to conduct BLCA with Markov chain Monte Carlo simulation to identify distinct latent clusters of managers' OST. This framework is consistent with

Costa and colleagues (2013). Solutions were tested through 2 to 8 clusters using approximately 55,500 samples and were compared against all fit-indices provided by AMOS, including the Gelman and colleagues (2004) convergence criteria, Posterior Predictive P-value (PPP), and Nagin's (2005) criteria of posterior probabilities for correct cluster assignment.

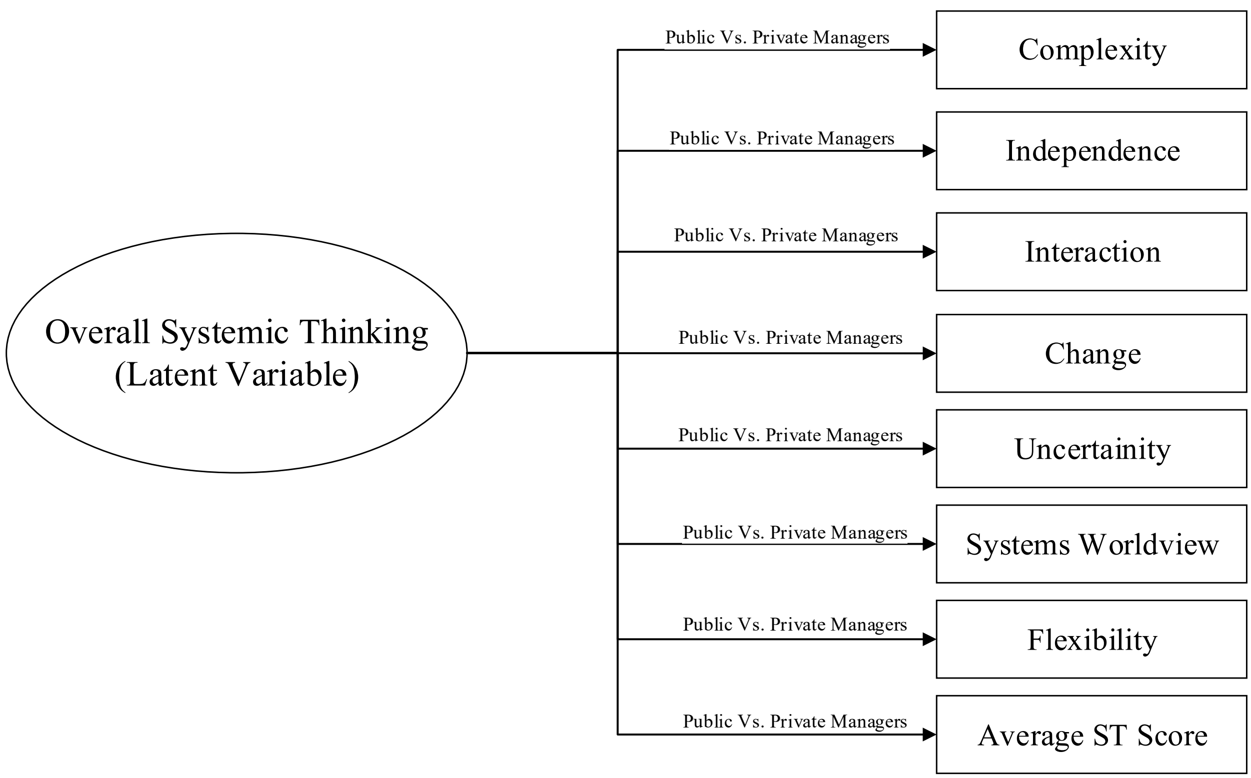

Figure 5.2 Overall Systemic Thinking Measured by Seven Dimensions of ST Skills

The 2-cluster solution resulted in the best convergence statistic (CS) of 1.0001 among all the solutions according to Costa, et al.'s recommendation (2013, p. 2): "CS, as it approaches 1.000 there is not much more precision to be gained." The 2-cluster solution also satisfies the Gelman and colleagues (2004) convergence criteria of < 1.002, and the best PPP of 0.61 among other solutions. For the 2-cluster solution, 49 out of 51 (around 96 percent clustering accuracy) cases were correctly clustered with the average posterior probabilities ranged between 0.75 to 1.00, suggesting good clustering accuracy and exceeding Nagin's (2005) criterion of > 0.70. The results indicate that the 2-cluster solution provided better convergence and accuracy than other solutions, which means other clusters are not permissible for the dataset. Table 5.3 presents the result of different cluster solutions using the BLCA method.

Table 5.3 Clustering Analysis Using BLCA Method

Solution	CS	PPP	Converged	Accuracy (%)
2-cluster*	1.0001	0.61	Yes	96
3-cluster	1.0012	0.72	Yes	92
4-cluster	> 1.002	0.76	No	90
5-cluster	> 1.002	0.80	No	76
6-cluster	> 1.002	0.84	No	74
7-cluster	> 1.002	0.87	No	71
8-cluster	> 1.002	0.90	No	70

*The best solution.

Since the 2-cluster solution fits the data better than the other cluster solutions, the managers' ST skills were classified into two distinct clusters, including the holistic managers (cluster with upper OST) and reductionist managers (cluster with lower OST). Table 5.4 shows the descriptive statistics of the 2-cluster solution with two distinct clusters—upper OST and lower OST.

Table 5.4 Two-Cluster Solution of Managers' OST

ST Dimensions	Lower OST Cluster *N = 23* *M*(*SD*)	Upper OST Cluster *N = 28* *M*(*SD*)
Complexity	76.4(5.7)	44.4(4.3)
Independence	62.7(6.4)	52.1(5.1)
Interaction	75.7(5.0)	57.4(4.4)
Change	65.9(4.4)	46.4(4.1)
Uncertainty	42.7(4.5)	22.8(4.2)
Worldview	77.1(7.2)	45.1(5.0)
Flexibility	78.2(6.4)	40.3(6.1)
Average	67.9(2.8)	44.0(2.4)

5.6.3 Binary Logistic Regression (BLR)

The logistic regression uses a binary or dichotomous variable as the dependent variable (Hosmer et al., 2013). BLR is a powerful multivariate analysis method that can predict the presence or absence of an outcome using a set of independent variables (Lee, 2005). Most importantly, logistic regression uses the maximum likelihood estimation that resists the violation of normality (Garson, 2012). Thus, the estimation of regression parameters are not detrimentally affected in BLR if the distribution of data is not extremely skewed or not multimodal (Mathew et al., 2007).

Initially, the average boundaries of the OST clusters were defined by BLCA method. We then tested whether we can classify and contrast managers' ST skills based on the public or private sector using BLR (with SPSS version 24.0). BLR calculates the likelihood of a specific case falling into a binary option by obtaining a set of independent variables. *Chi-square of 21.87 with eight degrees of freedom and p-value of 0.005 show that ST skills and average ST scores are effective in predicting the classification variable, which is sector type in this model*. Additionally, the small value of "-2 log likelihood," which is 44.35, indicates a good fit for the model (Keramati and Ardabili, 2011). We also found that the Nagelkerke's (1991) R-square is 0.48, which specifies the variables in the model predicted 48 percent of the variability in the two sectors. In sum, BLR can predict sector type as a classification variable with 78.4 percent accuracy based on the ST skills of the managers. In other words, managers working in the public sector have a different class of ST skills than managers in the private sector.

5.6.3.1 Hypothesis Testing

In accordance with Spatz's recommendation (2011), we performed four Tukey HSD post-hoc tests for each of the seven ST dimensions including average ST score to examine the differences between two classes of managers: public and private with regards to two identified clusters, upper OST and lower OST. The results indicate that the class of public managers is not significantly different from the upper OST cluster and is different from lower OST cluster in all dimensions except Independence. Likewise, the class of private managers is not significantly different from lower OST cluster and is different from the upper OST cluster in all dimensions except Independence. *Analysis results indicate that public managers' ST skills tend toward the upper OST (holistic) cluster, whereas private managers' ST skills tend toward the lower OST (reductionist) cluster*. In sum, all the study hypotheses are supported except H_2 (*Independence* dimension). Therefore, public managers have a different class of ST skills with respect to *Complexity* (H_1), *Interaction* (H_3), *Change* (H_4), *Uncertainty* (H_5), *Systems Worldview* (H_6), and

Flexibility (H_7) dimension, and also in terms of *Average ST Score (H_8)* compared with private managers (see Table 5.5).

Table 5.5 P-value results associated with Tukey HSD tests in 95% CI regarding seven ST dimensions and average ST score

Comparison between 4 groups*		**Comp.**[5]	**Ind.**[6]	**Int.**[7]	**Chan.**[8]	**Uncert.**[9]	**World.**[10]	**Flex.**[11]	**Average**[12]
Pub.[1] **Vs.**	**U**[3]	0.91	0.61	0.58	0.96	0.97	0.33	0.99	0.51
	L[4]	< .001	0.94	.04	< .001	< .001	< .01	< .001	< .001
Priv.[2] **Vs.**	**U**[3]	< .001	0.65	.02	< .001	< .001	< .001	< .001	< .001
	L[4]	0.71	0.78	0.58	0.98	0.80	0.32	0.77	0.21
Hypothesis		H_1	H_2	H_3	H_4	H_5	H_6	H_7	H_8
Hypothesis supported?		Yes	No	Yes	Yes	Yes	Yes	Yes	Yes

[1]Public managers, [2]Private managers, [3]Upper OST cluster, [4]Lower OST cluster, [5]Complexity, [6]Independence, [7]Interaction, [8]Change, [9]Uncertainty, [10]Systems Worldview, [11]Flexibility, [12]Average ST score.

5.7 Discussion and Implications

To show the OST boundaries for managers, their OST were clustered using the BLCA method into two distinct clusters: (1) the managers with upper OST and (2) the managers with lower OST. BLR then showed that managers' ST skills could be classified by the sector type with an accuracy of 78.4 percent. Comparison of these two clustering and classification methods yielded the interpretations shown in Figure 5.3, one of which is that both methods (i.e., clustering by BLCA and classification by BLR) similarly classified 75.5 percent of cases. This finding is consistent with the result of our hypothesis testing and validates the main result of the study – public and private managers have different ST skills. In sum, while the ST profile of public-sector managers with over 21 years of managerial experience tended toward the upper OST/holistic thinking cluster, the ST profile of private-sector managers with over 21 years of managerial experience tended toward the lower OST/reductionist thinking cluster. Figure 5.3 also shows more details of interest: e.g., the closest range of scores exists for the Independence dimension, whereas the highest range of scores belongs to the Flexibility dimension between public and private managers.

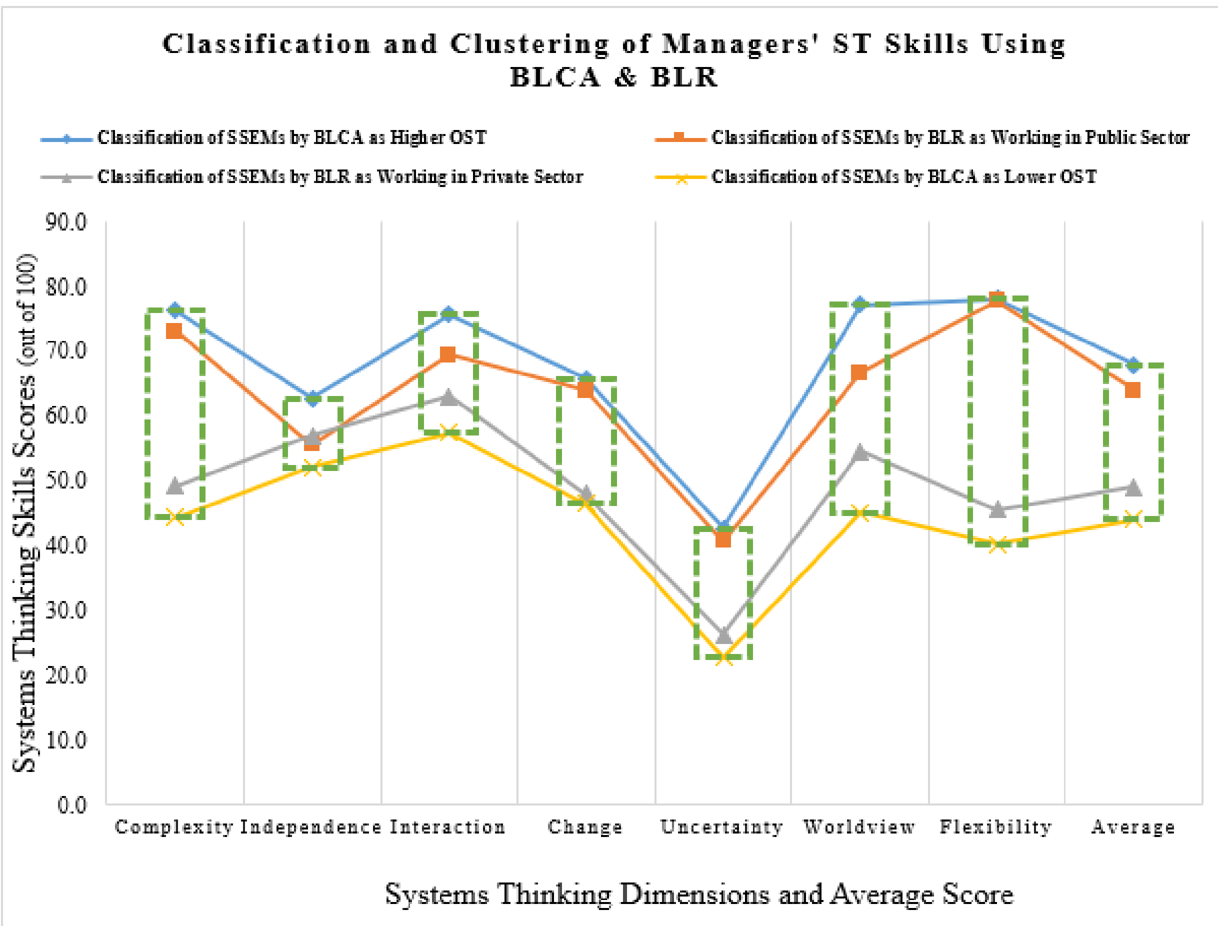

Figure 5.3 Classification and Clustering of Managers' ST Profiles

The Independence dimension defines whether or not an individual is comfortable working in a group. In both the public and private sector, there is still the desire for and expectation of working on teams. Similarly, managers are more inclined to work with the team they manage. Concerning the flexibility dimension, the public-sector managers typically exhibit much more flexibility since they are not held captive to shareholders, as are the private sector managers.

The ST profiles generated using the ST skills instrument represent an individual's ST capability, but it is important to stress that there are no inherently good or bad profiles. The relative value of a profile depends on the nature of the complex problem environment where an individual works. This environment influences his/her ST and cognitive-mapping capability and determines their personal preference toward a decision-making process.

In order to understand more about the results, we explored the existing literature and found that our results are consistent with other studies. Our findings also support the work of Borins (2000), Boyne (2002), Cats-Baril and Thompson (1995), Chen and Rainey (2014), Essig and Batran (2005), Gasik (2016), Gomes, et al., (2012), Jurisch et al. (2013), Kettl (1997, 2011), Kwak et al. (2014), O'Donovan (2011), PMI (2014), and Zokaei (2011) who all demonstrated that public-sector managers have different skills and tendencies than their counterparts in the private sector.

Contribution and validity of H_1: Public managers expect uncertainty, work on multidimensional problems, prefer a working solution, and explore the surrounding environment. On the contrary, private managers avoid uncertainty, work on linear problems, prefer the best solution, and prefer small-scale problems. This is consistent with the studies of Kettl (2011) and Boyne (2002), which posited that public managers deal with complex problems stemming from government rules and regulations, whereas private-sector managers engage with less complex problems as they can often define their organizational goals independently and have more freedom to manage their team.

Contribution and validity of H_2: Public and private managers both prefer global integration and tend more toward a dependent decision and global performance. They have the willingness and aptitude to make integrated decisions rather than autonomous decisions under fluctuating circumstances.

Contribution and validity of H_3: Since public organizations are structured more formally, public-sector managers and employees are more comfortable working as a team compared to their colleagues in the private sector. Moreover, personal formalization in the public sector works as a catalyst to facilitate teamwork and enhance coordination (Boyne, 2002). Private managers are inclined to local interaction, follow a detailed plan, prefer to work individually, enjoy working in small systems, and are interested more in cause-effect solution. Chen and Rainey (2014) also mentioned that teamwork is an essential element for public organizations as they need to constantly interact and share information with political parties, legislators, and interest groups. Therefore, public managers are more apt to work in a collaborative environment and can more easily adapt to any new environment.

Contribution and validity of H_4: Private managers prefer taking few perspectives into consideration, over-specify requirements, focus more on internal forces, like short-range plans, tend to settle things, and work best in a stable environment. A public organization needs to pursue a large number of goals that often need to be revised based on government interest, political affiliations, and legislation. Change in government and conflict of interest among the different stakeholders may compel public managers to accommodate a revised plan. These challenges make the public manager accustomed to working in a more dynamic and changing business environment.

This study finding is also consistent with Jurisch's et al. (2013) result that the public sector is constantly engaging with changing organizational processes to tackle social and political challenges.

Contribution and validity of H_5: Private managers prepare detailed plans beforehand, focus on the details, are uncomfortable with uncertainty, believe the work environment is under control, and enjoy objectivity and technical problems. Due to a large number of goals and change in government, rules and regulations may force public managers to fit work in a more dynamic and uncertain business environment. The private sector is less stable than the public sector because the organizational goals are more revenue driven. This statement is also supported by Essig and Batran (2005).

Contribution and validity of H_6: Public managers focus on the whole, are more interested in the big picture, and are more interested in concepts and the abstract meaning of ideas. By contrast, private managers focus on particulars and prefer analyzing the parts for better performance. For example, Borins (2000) stated that innovative public managers "are creatively solving public-sector problems and are usually proactive in that they deal with problems before they escalate to crises. They use appropriate organizational channels to build support for their ideas" (p. 498).

Contribution and validity of H7: Public managers are accommodating to change, like a flexible plan, are open to new ideas, and are unmotivated by routine. On the other hand, private managers prefer a determined plan, are open to new ideas, and are motivated by routine. Kettl (1997) also agreed that flexibility is a powerful skill for public managers to perform their tasks properly and to be accountable for the corresponding results.

Contribution and validity of H_8: In sum, public managers have more tendency toward systemic skills, whereas private managers have less inclination toward systemic skills. Because public-sector managers have to deal with a large number of stakeholders and are influenced by diverse external factors, they prefer to consider problems from multiple perspectives, focus more on external forces, work as a team, incline toward global integration, are comfortable with change and uncertainty, are interested in the big picture, are good at flexible plans, and remain open to options for further modifications. Several studies (e.g., Jaaron and Backhouse, 2011, 2014; O'Donovan, 2011; Zokaei, 2011) emphasize the necessity of a ST approach in public-sector management. They all agree that having appropriate ST skills and a holistic view can help public-sector managers handle their job requirements effectively.

The results of the study suggest several additional implications. First, the results provide more rigorous support for distinctions made between public and private sector managerial preferences. While the study must stop short of suggesting 'why' these differences exist, it is a substantial step forward to have a sound research basis supporting those claims. Additionally, the specific dimensions of distinction, breaking down ST to a more granular level of dimensions, provides insight into distinctions between public and private sector managerial skills. The study does suggest implications for: (1) recognition of different ST skills between public and private sector managers, (2) in examination of the appropriateness of a specific ST skill profile, consideration should be given as to the 'fit' of an individual with respect to public or private managerial role, and (3) given the distinction between public and private ST skills, care should be given to ensuring that those lacking sufficient skills for public/private sector success should receive professional development consideration, and (4) both public and private sector development should be cognizant of the shifting nature of work, the work environment, employees, and managerial skills as they will impact both public and private organizations in the future.

5.8 Conclusions

This study shows promising results in illustrating how the ST aptitude of managers varies depending upon the organizational ownership structure of public versus private sectors. Based on past research, a valid instrument for assessing ST was developed to measure an individual's predilection for ST skills when dealing with complex phenomena. In order to categorize the ST profile for each sector, seven dimensions (complexity, independence, interaction, change, uncertainty, systems worldview, and flexibility) were evaluated from the participant's response, and each sector characterizes a different ST profile. The first goal of this study was to cluster managers with 21+ years of managerial experience based on their overall systemic thinking (OST). The advanced data analysis showed that holistic and reductionist managers are distinct based on systems skill. This study's second goal was to classify them according to the organizational structure type—public and private sector using BLR. Data analysis indicated that public managers have different ST skills than private sector managers. The study's third goal was to investigate whether public and private managers belong to holistic or reductionist clusters. Comparative analyses showed that the ST skills of public managers tended toward the holistic thinker group (upper cluster of OST), whereas the ST skills of private-sector managers tended toward the reductionist thinker group (lower cluster of OST).

In this study effort, the distinction between public and private managers' systems thinking skills has been demonstrated. While this has been speculated and suggested in the literature, the study has provided a well-grounded and rigorously executed research design to support the conclusion of the distinction. Having established this distinction, three primary directions are suggested to improve managerial practices. First, knowing the propensity of a developing manager for systems thinking can offer important cues for professional fit and development. Given that public sector managers are more systems thinking skilled suggests the importance of ensuring that that capacity remains a focus throughout professional development. However, as complexity continues to increase rapidly, even the private sector managerial development would be well served to consider the importance of systems thinking to success of future managers. Second, consideration should be given to the interaction between public and private sector managers. While they may have different propensities for systems thinking capacity, each must interact with the other. Thus, the appreciation of differences in systems thinking (e.g. reductionist vs. holistic) can signal different levels and approaches for more successful interaction. Understanding the basis for different perspectives can lead to more effective interaction. To ignore the potential for misperceptions based on fundamental systems thinking differences can impede performance of both the public and private sectors. Third, the snapshot provided by this study represents a 'slice in time' and managers. With increasing complexity, environmental turbulence, and organizational shifts (e.g. demographics, culture, technology) the pressures related to increasing and shifting managerial skills may become more pronounced. Getting ahead of these shifts will require foresight. The more thorough examination of the nature and role that systems thinking skills might play for the future landscape of management is suggested. This applies to both the public and private sector, as both will experience major shifts in social, political, and technological future directions.

This study has also opened the door to further research and development. The study has identified the distinction between public and private sector managerial systems thinking skills. However, it does not provide an explanation as to why these distinctions exist, the source of the distinctions, and what enabling/limiting implications they suggest for the future of public and private sector management. Research directed to understanding these distinctions represent an important step in defining their implications and development of responsive development strategies. In addition, future studies could engage a larger sample of participants with equal size from different (sub)sectors of public and private organizations would be insightful and demonstrate the study findings' reliability and validity. Also, other organizational ownership structures, such as the non-profit sector, could be included in future studies as well. It is also of interest to possibly examine the nature of the future of work in relationship to systems thinking skills for both managerial as well as non-managerial workers. With rapid advances in the nature and performance of work, it cannot be assumed that managerial/non-managerial skills, including systems thinking skills, will remain static. Coming shifts (e.g. artificial intelligence, shifting demographics, and political/social change) may suggest investigation of different methods, tools, and techniques to classify managers based on the corresponding organizational ownership structure, and its results could be compared to the current study's results.

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