FOSTERING CREATIVITY IN ENGINEERING EDUCATION:

RELATIONSHIP OF DESIGN TASK DIFFICULTY TO SOLUTION NOVELTY

A Dissertation

by

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Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

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December 2017

Major Subject: Interdisciplinary Engineering

ABSTRACT

Conflicting claims about engineering students' abilities to innovate solutions to design tasks warranted evaluation of measures and clarification of roles of design task and student characteristics in developing innovative solutions. Three manuscripts clarified quality of measures and roles of design tasks and student characteristics using survey data from 361 students. The first manuscript evaluated measures of task difficulty, current achievement motivation and cognitive style using CFA, EFA and reliability analyses. Measures were found to have low validity and reliability. Future studies should be conducted with large sample sizes and improved item quality.

The second manuscript clarified roles of Grade Point Average (GPA), classification, major, task familiarity, current achievement motivation, and cognitive style in developing innovative solutions using decision tree analysis. GPA, major, current achievement motivation, and cognitive style were significant predictors of novelty. Eight combinations of students' characteristics that predict novelty of students' solutions to a design task were identified. Of the eight, four combinations predict conventional solutions. The remaining four combinations predict novel solutions. Stability of combinations and their thresholds should be verified with different design tasks and large sample sizes.

The third manuscript examined relationships of design task structuredness and complexity to novelty of solutions after controlling for GPA, major, challenge, anxiety, interest and novelty-seeking orientation. Structural equation modeling found significant positive association between structuredness and novelty, significant negative association between complexity and novelty, and significant positive correlation between structuredness and complexity. Only major 2 (BAEN, BMEN, CHEN, ETID, ISEN, NUEN, OCEN or PETE) was found significant relative to undeclared majors. Structuredness, complexity, major 2 explained 21% of the total variance in novelty. Findings support development of models to explain relationships between design tasks and abilities to innovate as moderated or mediated by student characteristics, controlling confounding effects of design tasks and students' characteristics in ideation studies, and discovery of strategies to develop students' abilities to innovate solutions.

DEDICATION

The Divine

ACKNOWLEDGEMENTS

I thank my PhD committee Co-Chair Jeffrey Froyd for his guidance and support of my PhD work. His constructive feedback was critical to preparing my dissertation proposal and completing a quality dissertation. I also thank K.R. Rajagopal (Chair), Bugrahan Yalvac (committee member) and Joyce Juntune (committee member) for their support of my work. In addition to my committee, I thank John Gero, Vimal Viswanathan, Matthew Ohland, and Homer Tolson for their feedback when I was formulating ideas for the dissertation study.

Further, I thank persons whose involvement was critical to data collection and data analysis. Specifically, I thank Yvonne Burrell for technical assistance in pre- and post-data collection phases. I thank Mark Troy for his help in setting up a Qualtrics account for this research. I also thank Prasad Enjeti, Jim Wilson, Rodney Boehm, Magda Lagoudas, Allen Godwin, Peter Hamilton, Richard Malak, Chuck Hsiao, Noushin Amini, Windy Lala, Timothy Jacobs, and the Engineering Innovation Center Committee for their help in recruiting participants. I thank my peers and engineering students enrolled at Texas A&M University during the 2015-2016 academic year for their participation in the pilot and dissertation study, respectively. I also thank Dori Wilson and Betsy Droddy for their assistance in processing participants' payments. Last, I thank Maria Henri, Homer Tolson, So Yoon Yoon, and Furong Li and Junho Yang with the Statistical Collaboration Center for their assistance with data analysis.

I also thank the University Writer Center experts, Valerie Balester, Candice Hastings, and Nancy Vazquez, for their advice during the writing of this dissertation.

Many thanks are also due to Interdisciplinary Engineering program chairs, Timothy Jacobs (current) and John Criscione (previous), staff, Matthew Pariyothorn, mentor, Robert Webb, and PhD committee members for conference travel support to present my dissertation and other work at the American Society for Engineering Education Conferences and Expositions. Their support was crucial to building a network of colleagues in my discipline and pursuing professional. service at the national. level.

Finally, I thank my family – my parents, Malkiat and Jasvir Rathore, husband, Karmvir Singh, and my sisters, Maanjot and Babandeep Rathore – for their emotional support. I also appreciate my colleagues and friends Ankit Patnaik and Ratika Gandhi, Yogesh Babbar, Priyanka Doshy, Gaurav Agarwal, Bernard Appiah, Cass Groen, Alaina Ruffin, Manoj Prasad, and others, for their support at various moments during graduate school.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supervised by dissertation committee members consisting of Dr. K.R. Rajagopal (advisor) of the Department of Mechanical. Engineering, Dr. Jeff Froyd (co-advisor) of the Department of Engineering Academic & Student Affairs, Dr. Bugrahan Yalvac of the Department of Teaching, Learning & Culture, and Dr. Joyce Juntune of the Department of Educational Psychology.

The analyses depicted in Chapters 3 and 4 were conducted in part by Mr. Junho Jang of the Department of Statistics.

All other work conducted for the dissertation was completed by the student, under the advisement of Dr. Jeff Froyd of the Department of Engineering Academic & Student Affairs.

Funding Sources

This work was made possible in part by funding from Dissertation Chairs, Drs. Jeff Froyd and K.R. Rajagopal.

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1. INTRODUCTION

Preparing engineering students with abilities to provide innovative solutions to increasingly challenging design problems is essential to their success as engineers. Though earlier studies (Atman, Chimka, Bursic, & Nachtmann, 1999; Cross, Christiaans, & Dorst, 1994) reported increases in students' abilities to innovate, recent studies (Lai, Roan, Greenberg, & Yang, 2008; Genco, Holta-Otto, & Conner Seepersad, 2012) suggested that students' abilities to provide innovative solutions diminish as they advance through the engineering curriculum. For example, in an earlier study Atman, et al. (1999), who measured creativity in terms of quantity of ideas generated, noted that final year students generated a higher quantity of ideas than second year students. Cross, et al. (1994) measured creativity in terms of quality of ideas generated and found senior students generated a higher quality of ideas than freshmen. In recent studies, Lai, et al. (2008) and Genco, et al. (2012) suggested that while both seniors and freshmen produced ideas of similar quality, seniors were less proficient than freshmen at creating original solutions to ill-defined problems using creative thinking. Conflicting claims about development of students' abilities to innovate through the curricula warranted research that clarifies roles of engineering curricula in developing their abilities to provide innovative solutions to challenging design problems.

While several aspects of engineering curricula may impact development of undergraduate students' abilities to innovate, this research focused on roles of instructor-assigned design tasks in advancing students' abilities to provide innovative solutions to challenging problems in the workplace. This is because instructor-assigned design tasks, which are presented typically in text format to students, form the crux of student experience in cornerstone and capstone courses in engineering (personal experience). Researchers have expressed needs to determine design task characteristics that make the tasks suitable for student learning (Jonassen & Hung, 2008); the needs remain unaddressed. Therefore, the relationships between assigned design task characteristics and undergraduate engineering students' abilities to innovate solutions to design tasks were examined in this dissertation after controlling for students' characteristics. Students' characteristics such as domain-relevant skills, cognitive style, and task motivation are posited as significant moderating and/or mediating variables of the creative process (Amabile, 2013).

No studies were found that examined relationships between characteristics of design tasks and engineering students' abilities to innovate with the control variables such as students' domain-relevant skills, cognitive style and task motivation as defined in this research. Previous research (Reiter-Palmon, et al., 2009 and Jo, et al., 2012) were limited to non-engineering design tasks with students and employees outside of the domain of engineering. In addition, the authors' mapping of the characteristics of the task was limited to problem difficulty measured only in terms of task complexity. Understandably, and given the purpose of their studies, Reiter-Palmon, et al. (2009) and Jo, et al.'s (2012) studies did not use a creativity index specific to the domain of engineering; metrics used to measure creativity can affect conclusions associated with a study. Martinsen and Kaufmann (2000) did not measure the creative performance of individuals in their study on effects of task motivation and A-E cognitive style on problem-solving performance. Therefore, this research examined relationships between design task characteristics and abilities to innovate with a design task, a more encompassing definition of design task characteristics, a creativity measure specific to the domain of engineering (Sarkar & Chakrabarti, 2011) and control variables and population unexamined in previous research.

Examining proposed relationships, however, required definition, development and/or evaluation of measures of design task characteristics, students' characteristics, and innovative solutions for present research. While many definitions and methods of measurement of task characteristics (Campbell, 1988; Kim & Soergel, 2005), student characteristics (Amabile, 2013; Lee, 2004) and students' abilities to innovate solutions (Sarkar, et al., 2011) exist in the literature, present research defined and measured task characteristics, students' characteristics, and innovative solutions in the following ways. Task difficulty, which according to Jonassen et al. (2008) can be viewed as a combination of task structuredness and task complexity and appears to encompass majority of the features of a task, was chosen to represent the characteristics of a design task. Task difficulty was measured using a 14 items Likert-scale that measures students' perceptions of task structuredness and task complexity. See Appendix A.

Domain-relevant skills, task motivation, and creativity-relevant processes, which impact students' abilities to innovate solutions to design tasks (Amabile, 2013), were chosen to represent students' characteristics. Domain-relevant skills were estimated from students' Grade Point Average (GPA), classification, familiarity with design task, and discipline. GPA is defined as the number of grade points earned divided by number of credit hours attempted (Registrar's office, 2014). Classification is defined as the number of attempted credit hours (Student Rule 13, 2014), and discipline is defined as major affiliation. Students self-reported their GPA, classification and discipline.

Task motivation was estimated from current achievement motivation, which is defined as achievement on a task as mitigated by task characteristics. This is because Freund, Kuhn, and Holling (2011), who examined measurement issues of the task motivation instrument used in this study, argue that interest - an indicator of current achievement motivation - is a significant predictor of creativity. Task motivation was measured using a short Questionnaire of Current Achievement Motivation. Only this questionnaire was found to measure students' motivation with respect to a given task. See Appendix B.

Creativity-relevant processes were estimated from students' cognitive style. Cognitive style, which is defined as individual differences in orientation towards different problem-solving strategies used to solve a task (Martinsen & Kaufmann, 2011), correlates with personality traits and is expected to explain variance beyond that of personality traits (Martinsen & Kaufmann, 2011). Cognitive style was measured using the Assimilator-Explorer (A-E) inventory. Given prior evidence of its validity and reliability and easy/free access, the A-E inventory is used in this research. See Appendix C.

Novelty - defined as something new/original (Sarkar et al., 2011) – of solutions to design tasks was chosen to represent students' abilities to provide innovative solutions.

While several definitions and methods to measure innovative abilities exist in the literature (Cropley, 2011; O'Quin & Besermer, 2011; Sarkar et al., 2011), abilities to innovate are commonly defined in terms of novelty and usefulness of solutions in engineering. Of the two, only novelty is chosen to represent students' abilities to innovate because recent literature (Lai, et al., 2008 & Genco, et al., 2012) suggested that originality of student-generated solutions diminishes as undergraduate students advance through the engineering curriculum. Novelty was estimated from newness of students' solutions to a design task based on rarity of solutions found in the sample (Verhaegen, Vandevenne, & Duflou, 2012)

The researcher did not find any need to evaluate selected measures of domain-relevant skills and innovative abilities, however, measures of task difficulty, task motivation and cognitive style were evaluated in present research. Section 2/manuscript #1 of this dissertation presents an evaluation of the psychometric properties of the three measures using confirmatory and exploratory factor analyses and reliability analyses. The purpose of this evaluation was to determine usability of the three measures for research on engineering students' abilities to innovate solutions to engineering design problems.

Section 2 contributes to the literature in three ways. First, it develops and evaluates new, domain-general measures of task difficulty for an engineering task. Doing so is critical for measuring task difficulty in research studies, doing cross-study comparisons using different design problems, and decreasing time invested in conducting future research with focus on examining students' perceptions of difficulty of curricula.

Second, it re-evaluates measures of current achievement motivation for an engineering task and measures of current achievement motivation and cognitive style with a sample of undergraduate engineering students from a large, research extensive, public university in the southern United States. Re-evaluation of measures with a sample from different populations and domains is critical for confirming generalizability of measures and subsequent use in research with new populations and domains (Hong, Purzer, & Cardella, 2011). Third, it evaluates all three measures using “new” statistical methods. Unlike previous research and consistent with current trends (S. Yoon Yoon, personal communication, early 2017) data obtained from Likert-scales was assumed to be of ordinal (and not continuous) scale. This assumption resulted in use of techniques and findings that may be different from previous research.

Further, examining proposed relationships required understanding how engineering students’ characteristics combine to predict their abilities to innovate solutions to design tasks. Characteristics such as an individual’s domain expertise, creativity-relevant skills, and motivation individually have been linked to creative performance in previous research (Amabile, 2013; Jo & Lee, 2012; Martinsen & Diseth, 2011). Section 3/manuscript #2 describes how GPA, classification, major, familiarity with a design task, current achievement motivation and cognitive style predict novelty solutions to a design task. This study is unique in its use of a model that accounts for combined roles of domain expertise, creativity-relevant processes and task motivation using decision tree analysis for predicting students’ abilities to generate innovative solutions to challenging design tasks. A purpose of this examination was to determine and prioritize the most important/significant characteristics for use as covariates - when studying the relationships between task difficulty and novelty – given the large number of measures, small sample size, and limited resources to collect additional data. In addition, moderating or mediating influences of students' characteristics were found from this analysis.

Section 3 informs the literature in three ways. One, it verifies relationships outlined among domain expertise, motivation and creativity relevant processes in Amabile's componential theory of creativity (2013), thereby giving strength to evidence for future use of Amabile's theory to frame research studies on creativity in engineering education. Two, it clarifies importance design education studies can assign to students' characteristics when comparing advantages and disadvantages of different ideation techniques in design research studies. Three, it provides hypotheses for future research on conditions which support/do not support novelty in student-generated solutions to design problems. Testing hypotheses is essential for developing instructional strategies engineering programs can use to enhance students' abilities to generate innovative solutions to challenging design problems.

Relationships between design task difficulty and novelty were explored after adequacy of measures and significant covariates were established for this research. Specifically, the direct effects of engineering students' perceived structuredness and complexity of an engineering design task on novelty of solutions were determined using structural equation modeling. Controlled covariates included GPA, major, perceived task challenge, task-related anxiety, interest in task and novelty-seeking orientation. Section

4/manuscript #3 describes findings from a preliminary model of associations between structuredness, complexity, significant covariates, and novelty of solutions for an engineering design task.

Section 4 has a three-fold contribution to engineering education. One, it provides a preliminary model and empirical evidence to build theories that eventually explain the relationship between problem characteristics and creativity as moderated and/or mediated by student characteristics. Two, it clarifies potential variance in observed novelty of solutions that design researchers can assign to both design problems and student characteristics when comparing advantages and disadvantages of different ideation techniques in design research studies. Three, it provides findings about conditions (e.g., characteristics of design task, students) which support novelty in student-generated solutions. Such findings can inform engineering programs and book publishers about strategies to develop students' abilities to innovate solutions to challenging design problems.

2. PSYCHOMETRIC EVALUATION OF MEASURES OF ENGINEERING DESIGN TASK DIFFICULTY, CURRENT ACHIEVEMENT MOTIVATION AND COGNITIVE STYLE

2.1 Introduction

The abilities to design innovative systems, components, or processes in response to increasingly challenging engineering problems and within realistic constraints are recognized as necessary competencies of students graduating from engineering programs (ABET, 2017). Previous research (Atman, Chimka, Bursic & Nachtmann, 1999; Cross, Christiaans & Dorst, 1994) reported increased abilities to innovate solutions to design problems. Recent research (Lai, Roan, Greenberg & Yang, 2008; Genco, Holtta-Otto & Seepersad, 2012), however, suggested that undergraduate students' abilities to innovate diminish as they advance through engineering curricula. Conflicting claims about development of students' abilities to innovate through the curricula warrant research that clarifies roles of engineering curricula in developing their abilities to provide innovative solutions to challenging design problems. Clarifying the roles of curricula, however, requires development and evaluation of measures that explore how students interact with the engineering curricula.

While research is needed to develop and evaluate many measures of students' interactions with the engineering curricula, this research furthers the development and evaluation of the following three measures: (a) students' perceptions of the difficulty of the curricula (i.e., task difficulty), (b) students' motivation to engage with the curricula (i.e., current achievement motivation), and (c) students' approach to problem solving (i.e., cognitive style) when faced with the curricula. Task difficulty, current achievement motivation and cognitive style have been linked to students' performance in technical and non-technical contexts (e.g., Freund, Kuhn & Holling, 2011). Therefore, development and evaluation of the psychometric properties of these three measures of students' interactions with the engineering curricula is essential to advancing research and practice in engineering education, especially as it relates to developing students' abilities to innovate in engineering.

2.1.1 Task difficulty

2.1.1.1 Definition

While there is no consensus in the literature on a definition of task difficulty (Campbell, 1988; Kim & Soergel, 2005), recent studies (Jonassen & Hung, 2008) have proposed that researchers examining the effects of task characteristics on learning outcomes consider task difficulty a combination of structuredness and complexity. The structuredness of a task can fall on a continuum of well-structured and ill-structured task (Lee, 2004). A well-structured task has a "clear statement of problem's components, one single correct solution, algorithmic paths to reach the goal, and application of a finite number of concepts, rules, and principles to constrain the situation." An ill-structured task "lacks one or more of problem components, is difficult to define, [and] possesses multiple solutions and paths to reach the goal." (p. 26-28). The complexity of a task can fall on a continuum that ranges from a simple task to a complex task. A simple task requires application of linear, straightforward reasoning using a small number of concrete concepts that take a short amount of time to solve. A complex task requires the use of relationally complex thinking involving abstract concepts, a large amount of conceptual and applied knowledge to solve the task, and more time than a simple task to find a solution. (Lee, 2004) In present research, task difficulty, therefore, has been conceptualized as students' perceptions of structuredness and complexity of an engineering task.

2.1.1.2 Factor structure

Task difficulty has been hypothesized as a two-factor model with task structuredness and task complexity as factors. See Jonnasen and Hung (2008) for a description of potential sub-factors of structuredness and complexity not considered in this research. Based on previous research (Lee, 2004), structuredness and complexity are expected to correlate with each other.

2.1.1.3 Measures

A measurement scale of task difficulty (14 items) was developed in this research using a combination of two 7 item, 5-point Likert-scales that measure task structuredness and task complexity, respectively, with labels of "disagree" at 1 and "agree" at 5. The new scale was developed for this research because the two existing measures (Jacobs, Dolmans, Wolfhagen & Scherpbier, 2003; Pierrakos, Zilberberg & Anderson, 2010) that were identified to have basis in the two-factor conceptualization of task difficulty were unsuitable for gauging students' perceptions of task difficulty for present research. The first of two measures (12-items scale), which was tested with a sample of 244 first year medical school students in Netherlands (Jacobs et al., 2003), was reported to have a good model fit. Contrary to the expected two-factor structure, a three-factor model with average to poor factor reliabilities was identified in previous research during model fitting. The second mixed-item measurement scale (Pierrakos et al., 2010) contains items that are context specific to undergraduate research. This scale is therefore non-applicable in studies where researchers desire to gauge students' perceptions of task difficulty prior to engaging with concept generation for assigned design tasks outside the undergraduate research experience context. The combined 14 item, 5-point Likert-scale, which consists of two sub-scales, is generic, face valid and content valid. In addition, previous research (Lee, 2004) indicated that reliability of participants' responses to the two chosen scales was fair. The Cronbach's alpha reliabilities of two sub-scales have been reported as 0.78 and 0.72, respectively (Lee, 2004).

2.1.2 Current achievement motivation

2.1.2.1 Definition

Current Achievement Motivation (CAM) is defined as student's achievement on a task as mitigated by task characteristics (Freund et al., 2011). CAM was conceptualized to explain the need for achievement that affects human behaviors when encountered with a specific task. CAM has its basis in the expanded cognitive model of motivation. This model of motivation predicts a learner's "tendency to perform an action that produces a desired consequence via an intended outcome" (Vollmeyer & Rheinberg, 2006, p. 8).

2.1.2.2 Factor structure

CAM has been formulated as a four-factor model with anxiety, challenge, interest and probability of success as factors. In this model, anxiety reflects “fear of failure in an achievement situation.” (p. 629). Challenge is “the degree to which a person accepts a task as relevant.” The degree of relevance of a task for a person is “influenced by perceived task easiness” (p. 629). Interest “is related to a person’s positive affect toward and positive evaluation of a task” and determination of probability of success is based on individual comparisons of “perceived ability with perceived difficulty of the task” (p. 629). While almost zero ($r = 0.03$) correlation exists between anxiety and challenge, a moderate correlation ($r = -0.53$, $p < 0.01$) has been reported between challenge and interest. (Fruend, et al., 2011)

2.1.2.3 Measures

CAM is measured using a short Questionnaire on Current Motivation (QCM). The short QCM is composed of a 12 item 7-point Likert-scale that ranges from disagree at 1 to agree at 7. This measure of CAM was reduced from an 18-items scale that explains task performance on cognitive tasks to increase usability for research. A satisfactory model fit with anxiety, challenge, interest and probability of success as factors (Satorra-Bentler Chi-square statistic = 112.88, df = 54, $p < 0.01$, comparative fit index (CFI) = 0.95, Tucker-Lewis index (TLI) = 0.93, root mean square error of approximation (RMSEA) = 0.6 [90% CI: 0.05-0.08]) has been reported when tested with 350 secondary school and undergraduate university students rating a Latin Squares Task on the short QCM. The four factors have been measured with three items each. The

Cronbach's alpha reliabilities have been reported as 0.85 for anxiety, 0.86 for interest, 0.70 for challenge and 0.85 for probability of success. (Fruend et al., 2011)

2.1.3 Cognitive style

2.1.3.1 Definition

While several theories of cognitive style exist in the literature (Martinsen & Kaufmann, 2011), the Assimilator-Explorer (A-E) theory has been chosen to represent students' approach to problem-solving in engineering. The A-E theory defines cognitive style within a problem-solving framework as differences in student's orientation towards different problem-solving strategies used to solve a task. Further, the theory is purported to integrate well with theories of personality and achievement motivation (Martinsen, et al., 2011) and has measures that are readily available for non-commercial research use.

2.1.3.2 Factor structure

The A-E theory positions students on a style continuum that ranges from rule-conforming (left-end, assimilators) to novelty-seeking (right-end, explorers) behaviors of problem solving. According to Kaufmann (Martinsen, et al., 2011, p. 217), assimilators interpret "new events in terms of existing knowledge". Explorers "search for new types of solutions … without any external pressure to do so" (p. 217). Accommodators, with scores that lie at the center of the style continuum, combine the problem-solving behaviors of both assimilators and explorers (Martinsen & Kaufmann, 2000). Previous research has identified a three-factor model with rule orientation, planning and novelty seeking as facets of the A-E construct. The three factors explain students' preferences for rules, planning and novelty seeking behaviors during problem-solving and have been reported to correlate with each other (Martinsen & Diseth, 2011).

2.1.3.3 Measures

Cognitive style is measured using the revised 30 item A-E inventory that has its basis in the A-E cognitive style theory. The A-E inventory consists of two 5-point, Likert-scales that measure assimilator and explorer orientation, respectively, with labels of "strongly disagree" at 1 and "strongly agree" at 5 for each problem-solving behavioral statement. A satisfactory fit (Chi Square = 1616.17, df = 772, p = 0.0, NFI = 0.84, NNFI = 0.90, CFI = 0.91, GFI = 0.89, RMSEA = 0.051) with rules, planning and novelty seeking as factors has been reported when tested with a group of students and employees consisting of technical staff and inventors in Norway. The overall Cronbach's alpha reliability has been reported as 0.92. Individual factor alpha reliabilities have been reported as 0.91 for rule orientation, 0.83 for novelty seeking and 0.68 for planning. (Martinsen, et al., 2011)

2.1.4 Engineering curricula

While undergraduate engineering students' interactions with several aspects of engineering curricula may influence their development of abilities to innovate, this research specifically focuses on students' interactions with instructor-assigned design tasks. The assigned design tasks, which are presented typically in text format to students, form the crux of student experience in cornerstone and capstone courses in engineering (personal experience). The researcher assigned a "mixed wasted [sic] collection" design task to students in present research. The task, which required students to develop concepts to separate paper and plastic from a mixed waste collection, was presented as such:

> One of the different systems used for curbside recycling is “mixed wasted collection,” in which all recyclates are collected mixed and the desired material is then sorted out at a sorting facility. One difficult sorting task is separating paper and plastic, which is usually done by hand. Develop concepts that will enable removing paper or plastic from the mixed collection. (Cheong, Chiu, & Shu, 2010)

The researcher chose to use the mixed waste collection task because of its successful use in idea generation research. In addition, this task was expected to invoke large amounts of variations in students’ responses to perceptions of task difficulty, current achievement motivation and cognitive style. The large amounts of variations are important for distinguishing between clusters of correlated items that model different facets of the same construct. Given these characteristics, the design task was used to examine psychometric properties of the three measures of students’ interactions with the curricula.

2.2 Research Purpose and Questions

This research examined the psychometric properties of generic measures of engineering design task difficulty, current achievement motivation and cognitive style with a sample of engineering students rating an engineering design task. The purpose of this examination was to determine the usability of the three measures for research on students' abilities to innovate solutions to engineering design problems. The research questions that were posed are:

1. What is the construct validity of measures of engineering design task difficulty, current achievement motivation and cognitive style?
2. What is the reliability of engineering students' responses to measures of engineering design task difficulty, current achievement motivation and cognitive style?

This examination is unique for three reasons. First, it develops and evaluates new, domain-general measures of task difficulty for an engineering task. Doing so is critical for measuring task difficulty in research studies, doing cross-study comparisons using different design problems, and decreasing time invested in conducting future research with focus on examining students' perceptions of difficulty of curricula. Second, it re-evaluates previously evaluated measures of current achievement motivation for an engineering task and measures of current achievement motivation and cognitive style with a sample of undergraduate engineering students from a large, research extensive, public university in the southern United States. Re-evaluation of measures with a sample from different populations and domains is critical for confirming the generalizability of the measures before subsequent use in research with new populations and domains (Hong, Purzer, & Cardella, 2011). Third, it evaluates all three measures using "new" statistical methods. Unlike previous research and consistent with current trends (S. Yoon Yoon, personal communication, early 2017), data obtained from Likert-scales was assumed to be of ordinal (and not continuous) scale. This resulted in use of techniques and findings that may be different from previous research.

2.3 Methods

A combination of approaches was used to determine the construct validity of measures of task difficulty, current achievement motivation and cognitive style using data from a sample of engineering undergraduates from the target population. The approaches to research included item analysis, exploratory factor analysis and confirmatory factor analysis. Using this combination of approaches is necessary when theoretical frameworks are hypothetical and/or empirical research is sparse. Reliabilities of engineering undergraduates' responses to measures of task difficulty, current achievement motivation and cognitive style were estimated from ordinal alpha computations for each of the underlying factors in the factor structure.

2.3.1 Target population

The target population for this research study consisted of all undergraduate engineering students enrolled at a large, research extensive, public university in the southern United States during the 2015-2016 academic year. The average target population size was approximately 11263 students. Approximately 21% were females and 78% were males. The population consisted of freshmen (18% - 27%), sophomores (21%), juniors (19% - 22%) and seniors (32% - 38%) over the two semesters. The ranges in classification estimates reflect variability in enrollment over the two academic semesters. The approximate number of students affiliated with each department is presented in Table 2.1. (Texas A&M University – College Station, 2017) The mean

Grade Point Average (GPA) of students in the population is not accessible without institutional. permissions and therefore unknown for this research; however, it is presumed to fall between 0.0 and 4.0 because the university computes students' grade point average on a four-point scale.

Table 2.1. Departmental affiliation and approximate percentage of students in the target population during the 2015-2016 academic year

Department affiliation	Students (%)
Aerospace engineering	4
Biological and agricultural. engineering	Unknown
Biomedical engineering	2
Chemical engineering	5
Civil engineering	6
College of engineering	28 - 31
Computer science and engineering	8
Electrical and computer engineering	7
Engineering technology and industrial distribution	12 - 13
Industrial and systems engineering	7
Mechanical engineering	9
Nuclear engineering	2
Ocean engineering	1
Petroleum engineering	5

The target population for this study was selected out of interest from both the US government and industry and researcher's interest and convenience. Both the US government (US Department of Commerce, 2012) and industry have expressed interest in preparing engineering undergraduates with abilities to provide innovative solutions to challenging design problems encountered in the workplaces. Findings derived from research on this population addressed the needs expressed by both the government and industry. Further, present researcher identified needs in the literature to study this population. In addition, the target population was easily accessible via e-mails through the existing network of colleagues, in-person recruitment and experiment visits required of participants.

2.3.2. Recruitment and selection

Multiple tactics were used to recruit participants for this research study. First, engineering students of freshmen, sophomore, junior or senior classification were invited to participate in the study via the university bulk-e-mail system. Second, the research study was advertised to students via e-mails through their professors and presentations during class. Third, the researcher made visits to engineering classrooms, primarily capstone design in mechanical engineering, to recruit participants for the research study. The capstone design classrooms were chosen strategical.ly for their high enrollment of students with senior classification.

Students self-selected to participate in the research study using an online study invite form. Use of different recruitment tactics resulted in a participation interest rate of approximately 5 % (~ 600 students). Of the 5% who expressed interest in participating in this research, approximately 60 % visited the research site to participate in the study. Students who consented to participate at the research site constituted the study sample.

2.3.3. Participants

The study sample consisted of 361 undergraduate engineering students. This sample was randomly split in approximately half (sample 1, sample 2) for the purposes of this study. Characteristics of each sample are presented in Table 2.2. As seen from Table 2.2, both sample 1 and sample 2 consist of more mal.es than femal.es. This trend is consistent with the gender distribution observed in the target population. Freshmen and sophomores comprise most participants in both samples. Notably, the two lower-level university classification groups were more amenable to participation in research

Table 2.2. Participants' characteristics in the two randomly split-samples. Number of participants is 361.

	Sample 1 N = 180		Sample 2 N = 181	
Category	n	%	n	%
Gender				
Female	60	33.5	83	45.9
Male	119	66.1	98	54.1
Unknown	1	0.6	-	-
Classification				
Freshman	58	32.2	56	30.9
Sophomore	49	27.2	55	30.4
Junior	26	14.4	19	10.5
Senior	47	26.1	51	27.6
Department				
Aerospace engineering	7	3.9	8	4.4
Biological and agricultural engineering	-	-	1	0.6
Biomedical engineering	-	-	-	-
Chemical engineering	8	4.4	10	5.5
Civil engineering	6	3.3	5	2.8
College of engineering	34	18.9	39	21.5
Computer science and engineering	15	8.3	13	7.2
Electrical and computer engineering	16	8.9	13	7.2
Engineering technology & industrial distribution	5	2.8	10	5.5
Industrial and systems engineering	4	2.2	6	3.3
Mechanical engineering	74	41.1	69	38.1
Nuclear engineering	7	7.0	4	2.2
Ocean engineering	-	-	-	-
Petroleum engineering	4	2.2	3	1.7
Grade Point Average (GPA)				
Reported (on 4.0 scale)	149	82.8	154	85
Not reported	31	17.2	27	14.9
Mean (standard deviation)	3.2 (0.5)		3.2 (0.5)	
Median	3.3		3.3	
Mode	4.0		3.5	
Range	0.8 – 4.0		1.1 – 4.0	

than juniors and seniors in the population. The majority of participants in sample 1 and sample 2 are also affiliated with either the college of engineering or mechanical engineering. Those who were affiliated with the college of engineering are freshmen who had not yet chosen a major. A high number of mechanical engineering participants resulted from the focused recruitment. A mean GPA of 3.2 is reported for both samples. A mode GPA of 4.0 in sample 1 and 3.5 in sample 2 suggests that most students who participated in this research are high-achieving students.

2.3.4. Data collection

Data was collected from participants using a prospective, survey research design approach after obtaining permissions from the university's Institutional. Review Board. Participants completed an online survey after consenting to participate in this research. The survey consisted of three forced-choice categorical items, one forced-choice open-ended item and three forced-choice Likert-scales. Categorical and open-ended items captured demographics variables such as a student's gender (categorical), university classification (categorical), department affiliation (categorical), and GPA (open-ended). The three Likert-scales were measures of task difficulty, QCM, and A-E inventory, respectively. Participants rated their perceptions of task difficulty, motivation to engage with, and general approach to problem-solving in engineering for the assigned design task on the three Likert-scales. Participants received monetary compensation for completing the online survey.

2.3.5. Data analysis

Data analysis was conducted in three stages to determine the construct validity and reliability of measures of task difficulty, current achievement motivation and cognitive style. To run the three stage analyses, the sample (N = 361) was randomly split in approximately half of the total sample size. The resulting split-sample sizes are considered appropriate for the three stage analyses using the five observations to one item (5:1) rule of thumb (Zygmont & Smith, 2014). Stages 1-3 consisted of running a confirmatory factor analysis (sample 2), an item analysis (sample 1) and an exploratory factor analysis (sample 1), respectively. The multiple stage analyses are necessary to validate the underlying factor structures of the three measures. All analyses were completed using R (R Core Team, 2017).

A confirmatory factor analysis (CFA) (Rosseel, 2012) was conducted first using observed measures of task difficulty, task motivation, and cognitive style, respectively, from sample 2, to verify the factor structures found for each of the measures in the literature. The measures of task difficulty, task motivation and cognitive style are presented in Table 2.3 (Lee, 2004), Table 2.4 (Fruend, et al., 2011), and Table 2.5 (Martinesen, et al., 2011). Four fit indices were used to evaluate model fit to actual data. The fit indices are: Chi-Square test of fit and p-value, comparative fit index (CFI), Root Mean Squarer Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). A model was considered acceptable under the following conditions (Awang, 2012):

a. Chi-Square divided by degree of freedom (df) was lower than 3 and P-value was different from zero (greater than 0.05)

b. Comparative Fit Index (CFI) values were above 0.95 (ideal.) or 0.90 (traditional.) or 0.80 (sometimes permissible)

c. Root Mean Square Error of Approximation (RMSEA) values were less than 0.05 (good) or 0.05 – 0.10 (moderate)

d. Standardized Root Mean Square Residual. (SRMR) values were less than 0.09

Table 2.3. Fourteen observed measures of task difficulty. Sub-scales: structuredness and complexity. Scale created with items from (Lee, 2004)

Measure	Description of observed measures
Structuredness	
TD1	Clearly stated goals or outcomes
TD2	Clearly defined criteria for successful problem solving
TD3	Clearly stated constraints that prevent successful problem solving
TD4	A single correct answer
TD5	A prescribed solution path
TD6	Requires solver to make assumptions and define the problem
TD7	Falls within a predictable domain of knowledge
Complexity	
TD8	Exhibits the relationship between concepts and rules vaguely
TD9	Complex solutions to the problem
TD10	Confusion from inclusion of too many elements in the problem
TD11	Unclear coherence from presence of too many aspects
TD12	Inclusion of many concepts, rules and principles in the problem statement
TD13	Random combination of various aspects of the problem
TD14	Elements represented in too many ways

If the model was found acceptable, convergent and discriminant validity of factors were computed to further establish the validity of measures of task difficulty, task motivation and cognitive style. Convergent validity (Awang, 2012) was established if values for the Average Variance Extracted (AVE) were greater than 0.5 and composite reliability (CR) values of factors were greater than 0.7. Divergent validity (Awang, 2012) was established if the following conditions were met:

a. Maximum Shared Variance (MSV) was less than Average Variance Extracted (AVE)
b. Average Shared Variance (ASV) was less than AVE
c. Square root of AVE was greater than inter-construct correlations

An exploratory factor analysis (EFA) was followed to provide corroborative evidence for the CFA.

Table 2.4. Twelve observed measures of task motivation. Sub-scales: probability of success, anxiety, interest, challenge. * = item reversed. Items from (Fruend, et al., 2011) listed here for instructive purposes only.

Measure	Description of observed measures
Probability of success	
TM1	I think I am up to the difficulty of this task.
TM2*	I probably won't manage to do this task.
TM10	I think everyone could do well on this task.
Anxiety	
TM3	I feel under pressure to do this task well.
TM6	I am afraid I will make a fool out of myself.
TM9	It would be embarrassing to fail at this task.
Interest	
TM4	After having read the instruction, the task seems to be very interesting to me.
TM8	For tasks like this I do not need a reward, they are lots of fun anyhow.
TM12	I would work on this task even in my free time.
Challenge	
TM5	I am eager to see how I will perform in this task.
TM7	I am really going to try as hard as I can on this task.
TM11	If I can do this task, I will feel proud of myself.

Table 2.5. Thirty observed measures of cognitive style. Sub-scales: Rule orientation, Novelty seeking, and Planning. * = item reversed during analysis. Items from (Martinsen, et al., 2011) used for research and listed here for instructive purposes only.

Measure	Description of observed measures
Rule Orientation	
CS1*	I prefer detailed work which requires neatness and precision
CS2*	I prefer situation in which you have to stick to options that are tried and true
CS3*	I prefer to stick to what I know well
CS4*	I prefer to avoid major changes
CS5*	I work best in situation which are clear and straightforward
CS6*	I prefer situations in which you have to work according to specific rules
CS7*	I am best suited for work which requires precision and a systematic approach
CS8*	I prefer work with set routines
CS9*	I prefer to have clear guidelines to stick to in work
CS10*	I prefer to have systematic instruction when learning something new
CS11*	I am exceptionally precise and task-oriented in my work
CS12*	I mostly stick to accepted ideas
CS13*	I prefer to stick to a set plan when working or solving problems
CS14*	I most often try to use well-tried methods for solving problems
CS15*	When trying to solve a problem, I most often try to find new means of doing so
CS23*	I like situations in which you have to seek new knowledge actively
CS24*	I work best in complex situations
CS25*	I can change my opinions/ideas even if the situation does not require it
CS26*	I most like to investigate unchartered territory
CS30*	I prefer to plan and structure what I am to do
Novelty seeking	
CS12*	I mostly stick to accepted ideas
CS15*	When trying to solve a problem, I most often try to find new means of doing so
CS16	I quite like situations in which it is necessary to break with conventional. wisdom
CS17	I prefer to figure things out on my own when I am learning something new
CS18	I most often adopt a playful and curious approach to my work
CS19	I prefer to improvise in what I do

Table 2.5. Continued

Measure	Description of observed measures
CS20	I bubble with ideas when I am solving problems
CS21	I most like situations in which you have to violate established norms
CS22	I most like to work with things I don't know too well from before
CS23*	I like situations in which you have to seek new knowledge actively
CS24*	I work best in complex situations
CS25*	I can change my opinions/ideas even if the situation does not require it
CS26*	I most like to investigate unchartered territory
CS27	I like best to work with without a prearranged plan
CS29	I prefer working without any clear guidelines
Planning	
CS1*	I prefer detailed work which requires neatness and precision
CS7*	I am best suited for work which requires precision and a systematic approach
CS11*	I am exceptionally precise and task-oriented in my work
CS13*	I prefer to stick to a set plan when working or solving problems.
CS19	I prefer to improvise in what I do
CS23*	I like situations in which you have to seek new knowledge actively
CS25*	I can change my opinions/ideas even if the situation does not require it
CS27	I like best to work with without a prearranged plan
CS28	I often try things out without planning systematical.ly
CS29	I prefer working without any clear guidelines
CS30*	I prefer to plan and structure what I am to do

If the model was found unacceptable, an EFA (Matsunaga, 2010; Zygmont et al., 2014) was conducted following an item analysis (Revelle, 2016) with sample 1. The item analysis was run to determine the adequacy of the sample for the EFA. Data was scanned for missing values and multivariate outliers. Missing values were identified using a frequency analysis. Multivariate outliers were identified using Mahlabonis distance ($p < 0.001$); however, none were deleted because the researcher had no practical reason for eliminating outliers from the data. Item statistics, included item mean, standard deviation, median, range, skew, kurtosis, and standard errors of skew and kurtosis, were computed. Inter-item polychoric correlation matrices (Fox, 2016), item-total correlation coefficients, standardized ordinal alpha values of scales, and ordinal alpha-if-item-deleted values (Gadermann, Guhn, & Zumbo, 2012) were also estimated to determine item quality. Mardia's Test for multivariate normality (Korkmaz, Goksuluk, & Zararsiz, 2014) was performed for each measure to determine the preferred method of factor extraction.

The EFA was conducted to explore the underlying factor structures of measures of task difficulty, task motivation and cognitive style, respectively. Factor solutions were extracted from observed measures using the principal axis factoring method. A promax rotation (Bernaards & Jennrich, 2005) was applied to improve solution interpretability. Decisions about retaining the number of factors for a solution were based on convergence of estimates from four procedures and resulting model plausibility and parsimony. The four procedures that were run to determine the retention of factors were (Matsunaga, 2010; Zygmont et al., 2014):

a. *Kaiser's Eigenvalue Criteria*. Factors were retained if eigenvalues resulting from the principal axis factoring technique and a promax rotation were greater than 1
b. *Cattell's Scree Plot*. Factors were retained if they were within the "sharp bend" on the Scree plot and the communalities were greater than 0.30
c. *Parallel Analysis*. Factors were retained if eigenvalues resulting from the observed correlations matrix were greater than the eigenvalues resulting from a randomly generated correlation matrix of the same size

d. *Velicer's Minimum Average Partial. (MAP) Test*. Factors were retained based on the step that resulted in lowest average squared partial correlations

These procedures resulted in generation of eigenvalue tables and scree plots. Pattern matrices, including factor loadings, communalities, and uniqueness, were computed. Factor correlations and explained variances were estimated. Ordinal alpha values and ordinal alpha-if-item-deleted values were al.so computed to determine if any of the sub-scal.es could be refined. Factors were labeled based on the type of items that loaded on each factor.

2.4. Results

This section describes results from the CFA, EFA and item analysis for measures of task difficulty, task motivation, and cognitive style, respectively.

2.4.1. Task difficulty

Fit indices obtained from the CFA indicate that participants' responses did not support the presence of prescribed two-factor measurement model of task difficulty. For example, the Chi-Square fit index of 4.87, which resulted from a Chi-Square value of 370.23 (df = 76) and p-value of zero, is higher than the suggested threshold of 3. The CFI, RMSEA, and SRMR values of 0.87, 0.15, and 0.13, respectively, are also outside the acceptable thresholds.

Further, indices obtained from the CFA suggested that computation of values of AVE, MSV, ASV and CR was not warranted due to an ill-fitting model. This outcome furthered the necessity of running an EFA along with an item analysis to determine the factor structure and reliability of measures of task difficulty.

The item analysis, which consisted of frequency analysis, multivariate outlier analysis and descriptive analysis of measures of task difficulty, found no missing data and several outliers. A complete data set was a result of the forced-choice online survey. Item means, standard deviations, medians, ranges, skew and kurtosis, standard errors of skew and kurtosis, ordinal. alpha-if-item deleted, item-total. correlations, and inter-item polychoric correlations obtained from the descriptive analysis are presented in Table 2.6 and Table 2.7, respectively. A low overall standardized ordinal. alpha value of 0.63 was recorded.

Table 2.6. Item statistics (mean, standard deviation (SD), median, range, skew, kurtosis, standard error (SE), ordinal alpha-if-item deleted, and corrected item-total correlation) for the proposed task difficulty scale

Item	Mean	SD	Median	Range	Skew	Kurtosis	SE	Ordinal Alpha, Item Deleted	Item-Total Correlation
TD1	4.26	0.70	4.00	4.00	-1.26	3.33	0.05	0.68	-0.09
TD2	3.42	1.06	4.00	4.00	-0.40	-0.95	0.08	0.64	0.18
TD3	2.51	1.06	2.00	4.00	0.80	-0.23	0.08	0.59	0.51
TD4	1.58	0.95	1.00	4.00	1.95	3.59	0.07	0.58	0.61
TD5	2.26	1.11	2.00	4.00	0.72	-0.39	0.08	0.56	0.72
TD6	3.76	0.92	4.00	4.00	-0.83	0.37	0.07	0.65	0.10
TD7	3.49	0.86	4.00	4.00	-0.42	-0.43	0.06	0.64	0.16
TD8	3.27	0.81	3.00	4.00	-0.26	-0.38	0.06	0.66	0.00
TD9	3.12	0.98	3.00	4.00	0.08	-0.72	0.07	0.64	0.12
TD10	2.03	0.86	2.00	4.00	1.28	2.31	0.06	0.56	0.73
TD11	2.13	0.87	2.00	4.00	0.99	0.90	0.07	0.55	0.75
TD12	2.81	1.00	3.00	4.00	0.15	-0.92	0.07	0.61	0.32
TD13	2.03	0.78	2.00	3.00	0.58	0.17	0.06	0.59	0.50
TD14	2.60	0.94	2.00	4.00	0.27	-0.73	0.07	0.59	0.50

Descriptive analysis results suggested removal. of items TD1, TD2, TD6, TD7, TD8, and TD9 from further analysis as their presence may become problematic during factor and reliability analyses. However, such an action was problematic. As seen from the corrected item-total correlation values in Table 2.6, items TD1, TD2, and TD6-TD9 correlate poorly with the rest of items on the scale. Poorly correlated items may not load on any of the factors. In addition, standardized ordinal alpha-if-item-deleted values for TD1, TD2, and TD6-TD9 see an increase if any one of the items is removed from the scale. Therefore, reliability of participants' responses can be improved if problematic items are removed from the scale. Premature deletion of items, however, may result in elimination of facets/factors of task difficulty deemed important in the literature. Therefore, no items were removed prior to the EFA.

Table 2.7. Polychoric correlations for items on scale of task difficulty

	TD1	TD2	TD3	TD4	TD5	TD6	TD7	TD8	TD9	TD10	TD11	TD12	TD13	TD14
TD1	1.00													
TD2	0.47	1.00												
TD3	0.06	0.21	1.00											
TD4	-0.31	0.16	0.38	1.00										
TD5	-0.11	0.18	0.43	0.68	1.00									
TD6	-0.01	-0.18	0.04	-0.25	0.02	1.00								
TD7	0.15	0.23	-0.12	0.22	0.24	0.02	1.00							
TD8	0.12	-0.03	0.02	-0.14	-0.08	0.09	-0.01	1.00						
TD9	-0.14	0.02	-0.07	0.02	-0.04	0.07	0.05	0.02	1.00					
TD10	-0.33	-0.12	0.16	0.51	0.40	-0.02	-0.05	0.05	0.26	1.00				
TD11	-0.33	-0.14	0.31	0.47	0.51	0.14	-0.05	-0.08	0.10	0.78	1.00			
TD12	0.11	0.04	0.16	0.11	0.06	0.15	0.09	-0.13	0.08	0.27	0.25	1.00		
TD13	-0.31	-0.09	0.36	0.34	0.37	-0.03	-0.28	0.05	-0.05	0.57	0.59	0.08	1.00	
TD14	-0.31	-0.21	0.22	0.18	0.40	0.21	-0.02	-0.03	0.10	0.49	0.54	0.13	0.43	1.00

An observation of the inter-item polychoric correlation matrix (see Table 2.7) suggested use of EFA is appropriate to determine the factor structure of task difficulty. Modest to moderate correlations between items indicated the presence of underlying factors. For example, items TD3-TD5 modestly correlated with each other. Items TD10, TD11, TD13, and TD14 were al.so moderately correlated with each other. Further, item analysis indicated use of principal axis factoring using weighted least squares estimation as the method of factor extraction for the EFA. Non-zero skew and kurtosis values, especial.ly for items TD1, TD4, TD10, suggested violation of normality. Mardia's test confirmed the violation of multivariate normality, informing the use of principal axis factoring as method of factor extraction during the EFA.

Procedures for estimating the number of factors indicated extraction of multiple competing solutions (see Table 2.8). While Velicer's MAP minimized at the first step, suggesting retention of a single factor during the EFA, the eigenvalue greater than 1 criteria specified extraction of two factors. The number of factors before the "bend" in the scree plot (Figure 2.1), however, also supported extraction of two factors. Parallel analysis suggested retention of six factors for the EFA. Pattern matrices resulting from the extraction of one, two and six factors during EFA are presented in Table 2.9.

Table 2.8. (Eigenvalues from) Parallel analysis, Velicer's minimum average partial (MAP) correlations, and Eigenvalues (extracted using Principal Axis factoring) for the task difficulty scale

	Parallel Analysis		Velicer MAP	Eigenvalues
	Original Data	Simulated Data		
1	3.38	0.62	0.04	3.52
2	1.12	0.41	0.04	1.42
3	0.48	0.32	0.05	0.74
4	0.45	0.24	0.05	0.68
5	0.26	0.17	0.07	0.46
6	0.12	0.10	0.09	0.29

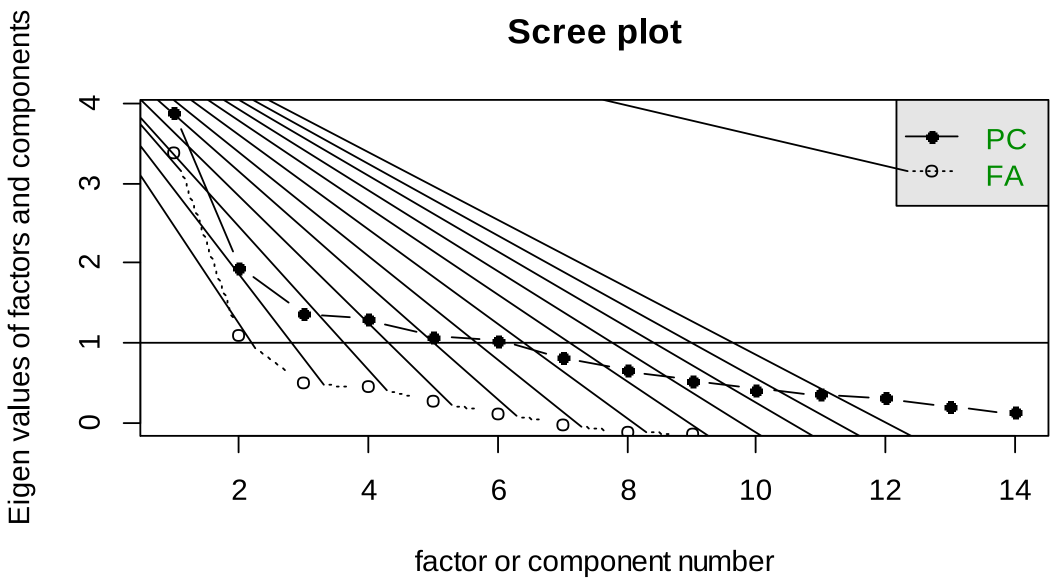

Figure 2.1. Scree plot suggesting extraction of 2 factors from observed measures of task difficulty

Analysis of the pattern matrices of a one, two and six-factor model suggested computation of a revised factor structure model of task difficulty based on a revised scale of its observed measures. As seen from Table 2.9, the pattern matrix of a single factor model revealed that items TD2, TD6-TD9, and TD12 do not load on the single factor when only one factor is extracted from the data. Non-loading items indicate poor item quality or need for extraction of additional factors. While the assertion of poor item quality may be supported by the presence of low inter-item correlations and item-total correlations, removal of items may result in loss of information regarding additional factors asserted both in the literature and evidenced by convergence of solutions from the Kaiser and Cattell criterion. Inspection of the pattern matrix of a two-factor model

Table 2.9.Pattern matrices resulting from extraction of one factor, two factors and six factors, respectively from 14 observed measures of task difficulty using principal axis factoring and promax rotation. Principal axis loadings = PA1, PA2…; h2 = communality; u2 = uniqueness. Blanks represent loadings < 0.3

	One Factor Model			Two Factor Model				Six Factor Model							
	PA1	h2	u2	PA1	PA2	h2	u2	PA1	PA2	PA3	PA4	PA5	PA6	h2	u2
TD1	-0.38	0.15	0.85		0.55	0.35	0.65		0.72					0.58	0.42
TD2		0.01	0.99		0.66	0.44	0.56		0.59					0.46	0.54
TD3	0.40	0.16	0.84	0.51		0.25	0.75	0.55						0.46	0.54
TD4	0.64	0.41	0.59	0.81		0.63	0.37	0.72			-0.43			0.80	0.20
TD5	0.64	0.41	0.59	0.82		0.64	0.36	0.80				0.38		0.72	0.28
TD6		0.00	1.00			0.04	0.96				0.62			0.32	0.68
TD7		0.00	1.00		0.35	0.13	0.87					0.63		0.40	0.60
TD8		0.00	1.00			0.01	0.99						0.48	0.20	0.80
TD9		0.01	0.99			0.02	0.98			0.43				0.18	0.82
TD10	0.81	0.66	0.34	0.62	-0.42	0.67	0.33	0.71		0.73				0.85	0.15
TD11	0.86	0.75	0.25	0.68	-0.42	0.75	0.25	0.74		0.35				0.77	0.23
TD12		0.04	0.96			0.05	0.95							0.28	0.72
TD13	0.67	0.44	0.56	0.50	-0.36	0.46	0.54	0.66				-0.34		0.61	0.39
TD14	0.59	0.34	0.66	0.39	-0.41	0.39	0.61	0.51			0.37			0.49	0.51

revealed that items TD2 and TD7 that did not load on a single factor model do indeed load in a two-factor model. Loading of previously non-loading items further supported non-plausibility of a single factor model of task difficulty. However, the two-factor model was also found to be problematic. Items TD6, TD8, TD9, and TD12 still did not load on the two-factor model. In addition, a two-factor model could not achieve a simple structure, courtesy multiple cross-loadings, making factor interpretation difficult. An examination of the pattern matrix of a six-factor model revealed similar problems to a two-factor model (e.g., missing item TD12, difficult interpretation of single item and cross-loading factors). Therefore, a new factor structure of task difficulty was computed based on removal. of items TD8 (zero item to total. correlation) and TD12 (non-loading). A re-run of procedures for estimating the number of factors after item elimination also indicated extraction of multiple competing solutions (see Table 2.10). While Parallel Analysis suggested extraction of 5 factors, the eigenvalue greater than or equal to 1 criteria suggested extraction of 3 factors. Velicer's MAP suggested extraction of a single factor. The bend in Scree plot (Figure 2.2) indicated that two factors should be extracted from the data. Therefore, solutions were examined for one, two, three, and five-factor solutions.

Table 2.10. (Eigenvalues from) Parallel analysis, Velicer's minimum average partial (MAP) correlations, and Eigenvalues (extracted using Principal Axis factoring) for the task difficulty scale after deletion of items which did not load on both the one factor and the two factor models.

	Parallel Analysis		Velicer MAP	Eigenvalues
	Original Data	Simulated Data		
1	3.32	0.53	0.06	3.66
2	1.05	0.30	0.06	1.71
3	0.36	0.21	0.08	1.04
4	0.15	0.14	0.10	0.68
5	0.09	0.06	0.14	0.56

After the examination of the one, two, three and five-factor solutions, a two-factor model appeared to best represent the factor structure of task difficulty. While both single and three factor solutions were found unacceptable for similar reasons to previous analysis, the five-factor model was found implausible based on presence of a Heywood case. The two-factor model, however, also suffered from non-loading items and multiple cross-loadings, making the solution less interpretable. Therefore, items TD6 and TD9 were removed from further analysis. Because the two-factor correlation was low (r = -

0.15), a varimax rotation was applied to help achieve a simple structure. A simpler two factor model resulting from the varimax rotation is presented in Table 2.11.

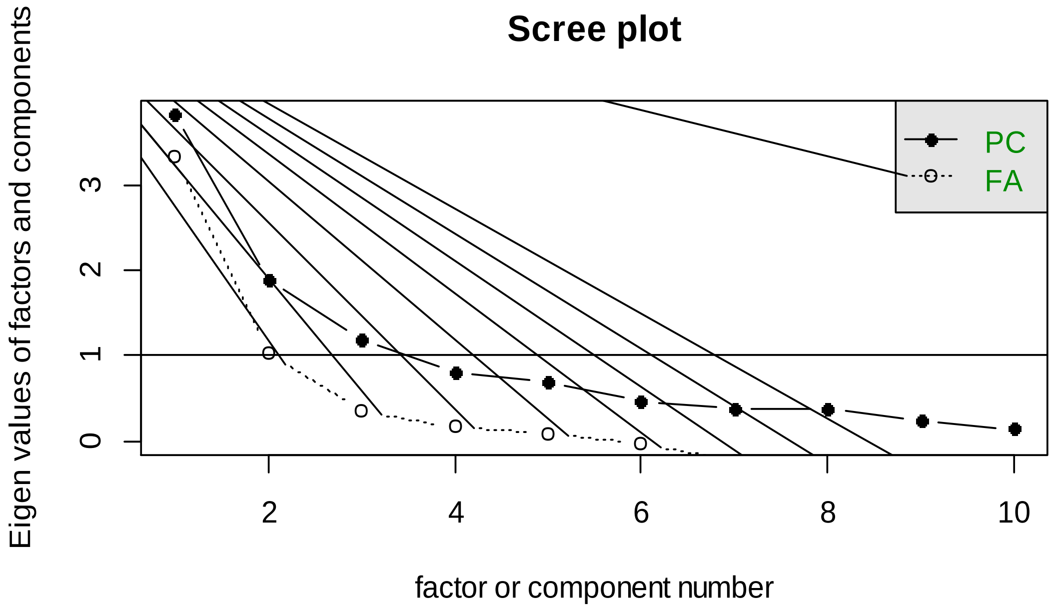

Figure 2.2. Scree plot suggesting extraction of 2 factors from observed measures of task difficulty

While an almost simple structure was achieved through a two-factor model for observed measures of task difficulty, it is difficult to propose meaningful factor labels consistent with definitions in the literature. Factor 1, which loads items TD1, TD3-TD5, TD10-TD11, and TD13-14, appears to represent some facets of structuredness and accounted for 35% of the explained variance with ordinal reliability of 0.84. Factor 2 appears to represent complexity and accounted for 15% of the explained variance. Ordinal reliability of factor 2 was found to be 0.54. The two-factor structure accounted for 49% of the total variance. As seen from Table 12, reliability of items which load on

Factor 1 may be improved to 0.85 if item TD3 is removed from the "structuredness" scale. Reliability can also be improved for Factor 2 through deletion of item TD7 on the "complexity" scale.

Table 2.11. Pattern matrix resulting from extraction of two factors from 14 observed measures of task difficulty using principal axis factoring and varimax rotation. Blanks represent loadings below 0.3.

	Factor 1	Factor 2	Communality	Uniqueness
TD1	-0.33	0.54	0.41	0.59
TD2		0.75	0.57	0.43
TD3	0.47		0.27	0.73
TD4	0.72		0.58	0.42
TD5	0.76	0.32	0.68	0.32
TD6	-	-	-	-
TD7		0.39	0.16	0.84
TD8	-	-	-	-
TD9	-	-	-	-
TD10	0.75		0.64	0.36
TD11	0.82		0.72	0.28
TD12	-	-	-	-
TD13	0.65		0.50	0.50
TD14	0.55		0.38	0.62

2.4.2. Task motivation

Fit indices obtained from the CFA suggested that participants' responses did not support the presence of a four-factor measurement model of task motivation. The Chi-Square fit index of 3.9, which resulted from a Chi-Square value of 187.28 (df = 48) and p-value of zero, is higher than the threshold value of 3. While the CFI value of 0.96 is higher than ideal., the RMSEA value of 0.13 was beyond the acceptable range. In addition, the SRMR value of 0.10 was only near acceptable the range for a well-fitting model. Given only one index met the well-fitting model criteria, the four-factor measurement model was deemed unacceptable. Values of AVE, MSV, ASV and CR were not computed.

Table 2.12. Standardized ordinal alpha-if-item deleted and item-to-total scale correlations for factors representative of task difficulty

	Ordinal Alpha	Item-Total Correlations
Factor 1		
TD1	-	-
TD3	0.85	0.46
TD4	0.82	0.67
TD5	0.81	0.72
TD10	0.81	0.77
TD11	0.8	0.83
TD13	0.82	0.66
TD14	0.84	0.56
Factor 2		
TD1	0.38	0.57
TD2	0.26	0.64
TD5	-	-
TD7	0.64	0.29

An EFA was run along with an item analysis to determine the actual. factor structure of and reliability of responses to measures of task motivation. The item analysis, which consisted of frequency analysis, multivariate outlier analysis and descriptive analysis of measures of task motivation, found no missing data and several. outliers. A complete data set was a result of the forced-choice online survey. Item means, standard deviations, medians, ranges, skew and kurtosis, standard errors of skew and kurtosis, ordinal alpha-if-item deleted, item-total correlations, and inter-item polychoric correlations obtained from the descriptive analysis are presented in Table 2.13 and Table 2.14, respectively. A modest overall standardized ordinal alpha value of 0.70 was recorded.

Table 2.13. Item statistics (mean, standard deviation (SD), median, range, skew, kurtosis, standard error (SE), ordinal alpha-if-item deleted, and corrected item-total correlation) for the scale of task motivation

Item	Mean	SD	Median	Range	Skew	Kurtosis	SE	Item-Total Correlation	Ordinal Alpha, Item Deleted
TM1	5.59	0.99	6.00	4.00	-0.83	0.74	0.07	0.38	0.69
TM2	5.06	1.32	5.00	6.00	-0.56	-0.39	0.10	0.18	0.71
TM3	3.96	1.74	4.00	6.00	-0.11	-1.32	0.13	0.19	0.71
TM4	4.90	1.43	5.00	6.00	-0.82	-0.03	0.11	0.72	0.63
TM5	5.26	1.32	5.00	6.00	-0.85	0.49	0.10	0.69	0.64
TM6	3.11	1.78	3.00	6.00	0.55	-0.91	0.13	0.34	0.70
TM7	5.47	1.24	6.00	6.00	-0.91	0.50	0.09	0.56	0.66
TM8	4.32	1.46	4.00	6.00	-0.16	-0.69	0.11	0.47	0.67
TM9	3.59	1.85	3.00	6.00	0.19	-1.25	0.14	0.20	0.71
TM10	3.91	1.63	4.00	6.00	-0.03	-1.00	0.12	0.19	0.70
TM11	5.48	1.19	6.00	6.00	-0.87	0.92	0.09	0.54	0.66
TM12	3.83	1.71	4.00	6.00	0.07	-1.09	0.13	0.68	0.64

Descriptive analysis results suggested running an EFA with principal axis factoring and weighted least squares as method of factor extraction for 12 measures of task motivation. As seen from Table 2.14, multiple items on the task motivation scale share a modest to moderate inter-item polychoric correlations with each other. For example, items TM1, TM2, TM4 and TM5 are modestly correlated with each other. Items TM4, TM5, TM7, TM8, TM11, and TM12 are also correlated with each other.

Presence of modest inter-item correlations indicates presence of an underlying factor structure that could be determined through an EFA. Skew and kurtosis values observed from Table 2.13 indicated that normality may be violated. Mardia's Test of multivariate normality confirmed violation of normality and use of principal axis factoring as the method of factor extraction. Ordinal alpha values and item-to-total correlations indicated that reliability of responses to measures of task motivation may be improved if items TM2, TM3, TM9 and TM10 are removed from the task motivation scale. However, none of these items were removed prior to the EFA to eliminate premature deletion of facets identified as important in the literature on task motivation.

Table 2.14. Polychoric correlations for items on the task motivation scale

	TM1	TM2	TM3	TM4	TM5	TM6	TM7	TM8	TM9	TM10	TM11	TM12
TM1	1.00											
TM2	0.51	1.00										
TM3	-0.22	-0.23	1.00									
TM4	0.32	0.10	-0.02	1.00								
TM5	0.38	0.12	0.07	0.69	1.00							
TM6	-0.28	-0.33	0.45	0.09	0.02	1.00						
TM7	0.08	0.07	0.19	0.45	0.51	0.15	1.00					
TM8	0.18	0.04	-0.02	0.48	0.44	0.00	0.28	1.00				
TM9	-0.08	-0.04	0.37	-0.12	-0.17	0.63	-0.05	-0.20	1.00			
TM10	0.21	0.10	-0.14	0.18	0.00	0.11	0.02	0.18	0.08	1.00		
TM11	0.08	0.10	0.20	0.34	0.36	0.17	0.46	0.20	0.10	-0.03	1.00	
TM12	0.28	0.11	0.03	0.57	0.52	0.12	0.34	0.50	-0.01	0.09	0.46	1.00

Procedures for estimating the number of factors (Table 2.15) led to extraction of two competing solutions. The Parallel Analysis suggested extraction of a five-factor solution. Velicer's MAP, the eigenvalues greater than or equal. to one criteria, and the scree plot (Figure 2.3) converged at a two-factor solution.

Table 2.15. (Eigenvalues from) Parallel analysis, Velicer's minimum average partial (MAP) correlations, and Eigenvalues (extracted using Principal Axis factoring) for the task motivation scale

	Parallel Analysis		Velicer MAP	Eigenvalues
	Original Data	Simulated Data		
1	2.93	0.63	0.04	2.95
2	1.39	0.36	0.04	1.81
3	0.41	0.27	0.05	0.74
4	0.30	0.17	0.06	0.44
5	0.14	0.11	0.08	0.16

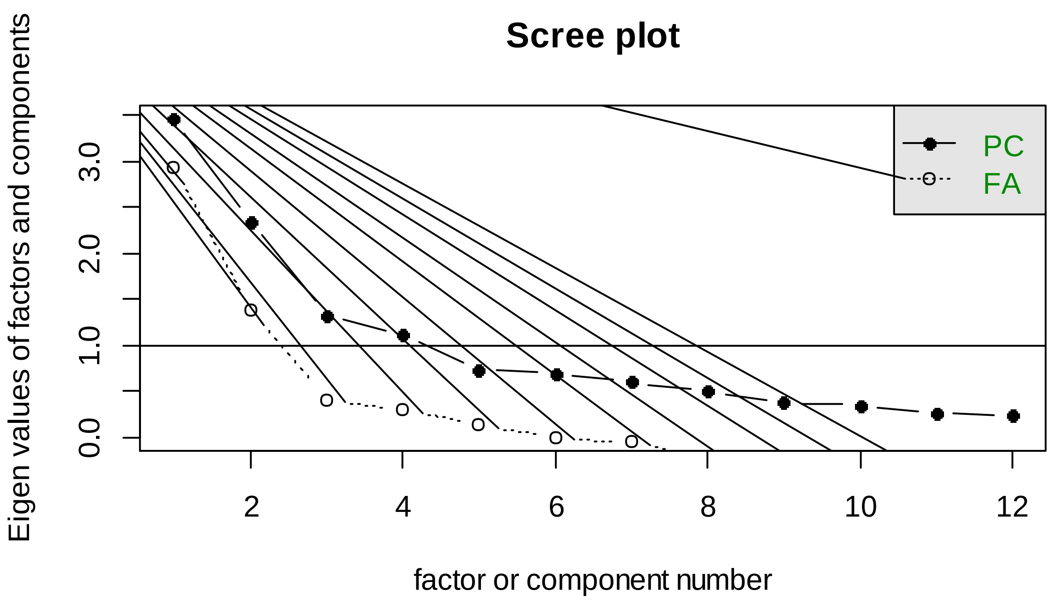

Figure 2.3.Scree plot suggesting extraction of 2 factors from observed measures of task motivation

The pattern matrix of the two-factor model of current achievement motivation is presented in Table 2.16 after disqualifying the five-factor model which rendered two of the five factors uninterpretable. The pattern matrix of this model presented an almost simple structure. Majority of the 12 items loaded on the first factor. Only one item cross-loaded on both factors. Expectedly, item TM10 did not load on the two-factor model after suppression of loadings under 0.30; the inter-item polychoric correlation matrix showed poor correlations between item TM10 and other items.

Table 2.16. Pattern matrix resulting from extraction of two factors from 12 observed measures of task motivation using principal axis factoring and promax rotation. Blanks represent loadings below 0.3.

	Factor 1	Factor 2	Communality	Uniqueness
TM1	0.39	-0.42	0.36	0.64
TM2		-0.40	0.21	0.79
TM3		0.58	0.34	0.66
TM4	0.79		0.63	0.37
TM5	0.79		0.63	0.37
TM6		0.81	0.65	0.35
TM7	0.59		0.37	0.63
TM8	0.56		0.33	0.67
TM9		0.62	0.40	0.60
TM10	-	-	0.02	0.98
TM11	0.53		0.32	0.68
TM12	0.72		0.51	0.49

Combined, the two factors accounted for 40% of the variability in participants' responses. Items loading on the first factor appeared to represent participants' positive reaction to the problem. Based on item representation, factor 1 was labeled "approach motivation." Approach motivation accounted for 25% of the variability in participants' responses and had responses with fairly high reliability (ordinal. value = 0.82). Items loading on the second factor appeared to represent participants' negative reaction to the problem. Therefore, factor 2 was labeled "avoidance motivation". The avoidance motivation factor accounted for 15% of the combined variance. Participants' responses to items loading on Factor 2 had low reliability as suggested by ordinal alpha value of 0.30. However, as seen from Table 17, scale reliability for the "avoidance motivation" factor may be improved if items TD1 and TD2 are removed from the scale. Factor correlations indicated a near zero, negative correlation (r = -0.08) between approach motivation and avoidance motivation.

Table 2.17. Standardized ordinal alpha-if-item deleted and item-to-total scale correlations for factors representative of task motivation

	Ordinal Alpha	Item-Total Correlations
Factor 1		
TM1		
TM4	0.77	0.78
TM5	0.77	0.77
TM7	0.81	0.60
TM8	0.82	0.56
TM11	0.82	0.54
TD12	0.78	0.72
Factor 2		
TM1	0.40	0.11
TM2	0.40	0.13
TM3	0.23	0.33
TM6	0.18	0.54
TM9	-0.08	0.72

2.4.3. Cognitive style

Fit indices obtained from the CFA suggest that participants' responses supported the presence of a three-factor measurement model for cognitive style. The Chi-Square fit index of 1.97, which resulted from a Chi-Square value of 760.86 (df = 386), is lower than the threshold value of 3 despite a p-value of zero. The CFI value of 0.94 was within the traditional.ly accepted values of CFI and the RMSEA value of 0.07 was also within the acceptable bounds of model fit. While the SRMR value of 0.09 was borderline acceptable, overall, the three-factor model was found acceptable on basis of multiple well-fitting model criteria.

Mixed results were obtained about the construct validity of and reliability of responses to measures of cognitive style. Judging the values of AVE, MSV, ASV, and CR (see Table 2.18) against the criterion for convergent and divergent validity and reliability indicated:

a. None of the factors are well-explained by their observed items (all AVE values < 0.5); i.e., all factors lack convergent validity
b. Observed items within a factor correlate more strongly with items outside the factor for both "Rules" and "Planning" (MSV > AVE, ASV > AVE and SQRT (ASV) < inter-construct correlations); i.e., both factors have weak divergent validity. Only "Novelty" has somewhat strong divergent validity
c. CR values indicated that participants' responses were fairly reliable (CR > 0.70).

Table 2.18. Values of AVE, MSV, ASV and CR and correlations between factors of cognitive style

Factor	Measures				Correlations		
	AVE	MSV	ASV	CR	Rules	Novelty	Planning
Rules	0.19	0.54	0.43	0.78	1		
Novelty	0.25	0.31	0.20	0.81	-0.56	1	
Planning	0.31	0.54	0.31	0.80	0.73	-0.30	1

An EFA was run along with an item analysis to determine the actual. factor structure of and reliability of responses to measures of cognitive style once factors were found to have weak convergent and divergent validity. The item analysis, which consisted of frequency analysis, multivariate outlier analysis and descriptive analysis of measures of cognitive style, found no missing data and several outliers. A complete data set was a result of the forced-choice online survey. Item means, standard deviations, medians, ranges, skew and kurtosis, standard errors of skew and kurtosis, ordinal alpha-if-item deleted, item-total correlations, and inter-item polychoric correlations obtained from the descriptive analysis are presented in Table 2.19 and Table 2.20, respectively. A modest overall standardized ordinal alpha value of 0.78 was recorded.

Descriptive analysis results suggested running an EFA with principal axis factoring as method of extraction on 30 measures of cognitive style. As seen from Table 2.20, multiple items on the cognitive style scale share a modest to moderate inter-item polychoric correlations with each other. For example, items CS2-CS8 and CS10 are correlated moderately with each other. Items CS18-CS22 are also correlated with each other. Presence of modest inter-item correlations indicates existence of an underlying structure that could be determined through an EFA. Non-zero values of skew and kurtosis observed from Table 2.19 indicated a possible normality violation. Mardia's Test of multivariate normality confirmed violation of normality and suggested use of principal axis factoring as the method of factor extraction. Ordinal alpha values and item-to-total correlations indicated that reliability of responses may be improved if items CS15, CS23, CS24-CS27 are removed from the cognitive style scale. However, none of these items were removed prior to the EFA to eliminate premature deletion of facets identified as important in the cognitive style literature.

Table 2.19. Item statistics (mean, standard deviation (SD), median, range, skew, kurtosis, standard error (SE), ordinal alpha-if-item deleted, and corrected item-total correlation) for the cognitive style scale

Item	Mean	SD	Median	Range	Skew	Kurtosis	SE	Item - Total Correlation	Ordinal Alpha, Item Deleted
CS1	2.04	0.81	2.00	4.00	0.75	0.72	0.06	0.30	0.78
CS2	2.64	0.91	3.00	4.00	0.29	-0.50	0.07	0.58	0.76
CS3	2.27	0.87	2.00	4.00	0.53	-0.09	0.06	0.58	0.76
CS4	2.88	1.00	3.00	4.00	0.01	-0.95	0.07	0.40	0.77
CS5	1.96	0.81	2.00	3.00	0.50	-0.35	0.06	0.63	0.76
CS6	2.77	1.04	3.00	4.00	0.17	-0.93	0.08	0.64	0.76
CS7	2.32	0.96	2.00	4.00	0.74	0.29	0.07	0.60	0.76
CS8	2.54	1.03	2.00	4.00	0.39	-0.61	0.08	0.69	0.76
CS9	2.36	0.93	2.00	4.00	0.74	0.24	0.07	0.63	0.76
CS10	1.94	0.92	2.00	4.00	1.14	1.23	0.07	0.60	0.76
CS11	2.41	0.97	2.00	4.00	0.38	-0.60	0.07	0.45	0.77
CS12	2.78	0.93	3.00	4.00	0.27	-0.61	0.07	0.55	0.76
CS13	2.34	0.87	2.00	4.00	0.86	0.55	0.06	0.60	0.76
CS14	2.18	0.81	2.00	4.00	0.78	0.66	0.06	0.62	0.76
CS15	2.78	0.99	3.00	4.00	0.06	-0.84	0.07	-0.21	0.80
CS16	3.51	1.01	4.00	4.00	-0.41	-0.56	0.07	0.43	0.77
CS17	3.57	1.08	4.00	4.00	-0.43	-0.59	0.08	0.28	0.78
CS18	3.61	1.04	4.00	4.00	-0.34	-0.73	0.08	0.34	0.77
CS19	3.32	1.07	3.50	4.00	-0.22	-0.91	0.08	0.53	0.77
CS20	3.48	0.96	4.00	4.00	-0.31	-0.68	0.07	0.30	0.78
CS21	2.93	1.07	3.00	4.00	0.08	-0.71	0.08	0.50	0.77
CS22	2.87	0.99	3.00	4.00	0.22	-0.61	0.07	0.50	0.77
CS23	2.12	0.77	2.00	3.00	0.65	0.37	0.06	-0.07	0.79
CS24	2.52	0.90	2.00	4.00	0.21	-0.61	0.07	-0.32	0.80
CS25	2.20	0.92	2.00	4.00	0.70	-0.10	0.07	-0.20	0.80
CS26	2.42	0.95	2.00	3.00	0.20	-0.89	0.07	-0.34	0.80
CS27	3.52	0.95	4.00	4.00	-0.48	-0.24	0.07	-0.55	0.81
CS28	3.13	1.11	3.00	4.00	-0.02	-1.09	0.08	0.43	0.77
CS29	2.49	1.00	2.00	4.00	0.57	-0.26	0.07	0.57	0.76
CS30	2.28	0.85	2.00	3.00	0.68	-0.11	0.06	0.42	0.77

Table 2.20. Polychoric correlations for items on the cognitive style scale

	CS1	CS2	CS3	CS4	CS5	CS6	CS7	CS8	CS9	CS10	CS11	CS12	CS13	CS14	CS15	CS16	CS17	CS18	CS19	CS20	CS21	CS22	CS23	CS24	CS25	CS26	CS27	CS28	CS29	CS30
CS1	1.00																													
CS2	0.24	1.00																												
CS3	0.12	0.47	1.00																											
CS4	0.01	0.31	0.45	1.00																										
CS5	0.12	0.42	0.55	0.31	1.00																									
CS6	0.19	0.46	0.34	0.28	0.49	1.00																								
CS7	0.30	0.34	0.13	0.17	0.34	0.48	1.00																							
CS8	0.15	0.39	0.39	0.31	0.44	0.57	0.50	1.00																						
CS9	0.08	0.29	0.38	0.27	0.32	0.47	0.28	0.51	1.00																					
CS10	-0.01	0.35	0.34	0.23	0.43	0.34	0.37	0.47	0.51	1.00																				
CS11	0.43	0.14	0.07	0.10	0.11	0.21	0.36	0.27	0.25	0.22	1.00																			
CS12	0.15	0.40	0.49	0.26	0.42	0.39	0.24	0.41	0.45	0.33	0.18	1.00																		
CS13	0.27	0.47	0.39	0.28	0.40	0.22	0.37	0.38	0.34	0.38	0.26	0.34	1.00																	
CS14	0.03	0.31	0.43	0.25	0.43	0.37	0.36	0.52	0.45	0.44	0.34	0.49	0.42	1.00																
CS15	0.15	0.01	-0.28	-0.34	-0.14	-0.18	-0.04	-0.14	-0.16	-0.07	0.14	-0.25	0.00	-0.28	1.00															
CS16	0.01	0.21	0.35	0.36	0.10	0.28	0.12	0.21	0.32	0.05	-0.07	0.33	0.20	0.16	-0.53	1.00														
CS17	-0.12	0.11	0.12	0.15	0.32	0.26	0.14	0.18	0.23	0.17	-0.10	0.07	0.09	0.12	-0.18	0.24	1.00													
CS18	-0.02	0.24	0.17	0.25	0.24	0.29	0.22	0.30	0.10	0.05	-0.01	0.22	0.28	0.12	-0.39	0.45	0.26	1.00												
CS19	0.04	0.21	0.20	0.37	0.18	0.34	0.19	0.38	0.37	0.19	0.16	0.26	0.25	0.21	-0.48	0.59	0.31	0.49	1.00											
CS20	-0.06	0.20	0.21	0.18	0.18	0.16	0.14	0.18	0.13	0.07	0.03	0.25	0.02	0.16	-0.32	0.40	0.20	0.32	0.43	1.00										
CS21	-0.03	0.14	0.31	0.24	0.23	0.28	0.19	0.25	0.24	0.16	0.11	0.27	0.17	0.26	-0.35	0.59	0.29	0.38	0.48	0.38	1.00									
CS22	-0.06	0.11	0.45	0.35	0.37	0.29	0.19	0.40	0.36	0.22	0.12	0.24	0.23	0.25	-0.36	0.47	0.38	0.36	0.49	0.24	0.51	1.00								
CS23	0.26	-0.03	-0.13	-0.24	-0.01	-0.10	0.02	-0.10	-0.08	0.22	0.24	0.02	0.02	-0.02	0.50	-0.44	-0.31	-0.36	-0.41	-0.41	-0.38	-0.51	1.00							
CS24	-0.02	-0.18	-0.31	-0.23	-0.39	-0.31	0.02	-0.28	-0.33	-0.10	0.02	-0.20	-0.08	-0.15	0.26	-0.30	-0.37	-0.29	-0.38	-0.28	-0.24	-0.41	0.35	1.00						
CS25	0.14	-0.05	-0.14	-0.21	-0.05	-0.08	-0.03	-0.17	-0.13	0.00	-0.05	-0.19	-0.18	-0.02	0.28	-0.27	-0.17	-0.35	-0.33	-0.14	-0.19	-0.33	0.27	0.23	1.00					
CS26	0.00	-0.22	-0.34	-0.38	-0.16	-0.31	-0.07	-0.22	-0.22	0.00	0.07	-0.33	-0.16	-0.13	0.47	-0.57	-0.28	-0.43	-0.51	-0.30	-0.53	-0.50	0.52	0.36	0.29	1.00				
CS27	-0.18	-0.38	-0.25	-0.18	-0.49	-0.47	-0.36	-0.44	-0.32	-0.32	-0.22	-0.39	-0.36	-0.41	0.06	-0.19	-0.06	-0.28	-0.17	-0.05	-0.22	-0.33	0.03	0.25	0.09	0.29	1.00			
CS28	0.16	0.18	0.17	0.17	0.17	0.28	0.30	0.19	0.14	0.08	0.20	0.05	0.22	0.16	-0.19	0.38	0.16	0.20	0.39	0.19	0.46	0.35	-0.29	-0.20	-0.35	-0.30	-0.27	1.00		
CS29	0.03	0.14	0.24	0.10	0.40	0.31	0.22	0.30	0.48	0.34	0.05	0.18	0.30	0.33	-0.16	0.33	0.22	0.25	0.49	0.21	0.49	0.46	-0.26	-0.16	-0.20	-0.25	-0.29	0.44	1.00	
CS30	0.28	0.22	0.09	0.01	0.22	0.25	0.24	0.28	0.23	0.21	0.43	0.05	0.29	0.20	0.15	0.03	0.06	0.04	0.16	-0.02	0.12	0.22	0.12	-0.10	-0.16	0.00	-0.53	0.47	0.27	1.00

Procedures for estimating the number of factors (Table 2.21) led to extraction of two competing solutions. The Parallel Analysis suggested extraction of a five-factor solution. Velicer's MAP, the eigenvalues greater than or equal. to one criteria, and the scree plot (Figure 2.4) converged at a three-factor solution.

Table 2.21. (Eigenvalues from) Parallel analysis, Velicer's minimum average partial (MAP) correlations, and Eigenvalues (extracted using Principal Axis factoring) for the cognitive style scale

	Parallel Analysis		Velicer MAP	Eigenvalues
	Original Data	Simulated Data		
1.00	7.78	0.95	0.03	8.01
2.00	2.97	0.75	0.02	3.27
3.00	1.10	0.65	0.02	1.44
4.00	0.66	0.57	0.02	0.94
5.00	0.51	0.51	0.02	0.78

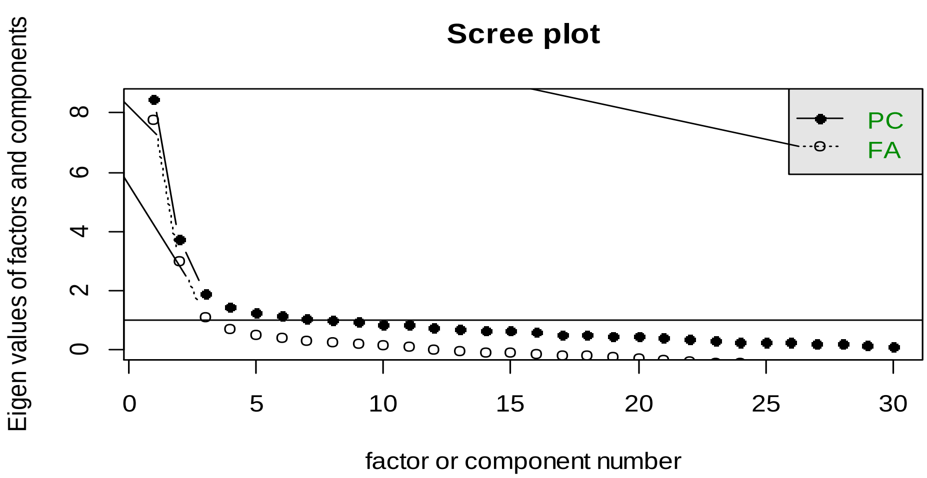

Figure 2.4. Scree plot suggesting extraction of 3 factors from observed measures of cognitive style

The three-factor model of cognitive style is presented in Table 2.22 after disqualifying a five-factor model that rendered two of the five factors uninterpretable. An almost simple pattern matrix emerged from the data. Items that are recommend for removal through an analysis of ordinal alpha-if-item-deleted and item-total correlations load modestly on the first factor. The negative loadings on items, however, suggest reverse coding to obtain consistency in measurement of factor 1. Item 27 could al.so be reverse-coded as it varies inversely with most of the items on Factor 2. Reversing item 27 could also “fix” Factor 3 so that all items load in the same direction on Factor 3. Pattern matrix also suggests removal of item 28 as it cross-loads on all factors and varies inversely with all items on Factor 2.

The three-factor model accounted for 42% of the total explained variance. Factor 1 and 2 contributed 17% each to the explained variance. Keeping with the literature (Martinsen, et al., 2011), Factor 1 and 2 were labeled “novelty” and “rules,” respectively. Factor 3, which accounted for 7% of the explained variance, was labeled planning. Factor correlations are reported in Table 2.23. As seen from Table 2.23, all factors correlated positively with each other. While planning and novelty were correlated poorly, both planning and rules and rules and novelty showed modest correlations with each other. Reliabilities of responses to items on factor 1 were found poor (ordinal. alpha = 0.095). Factor 3 showed modest reliability with an ordinal alpha value of 0.66 and Factor 2 had the highest reliability with an ordinal alpha value of 0.82. As seen from Table 2.24, low reliability of responses to items on Factor 1 may be a result of incorrectly coded items evident from negative alpha if-item-deleted values. Reliability of responses to items on Factor 2 may be improved to 0.88 by deleting item CS27.

Table 2.22. Pattern matrix resulting from extraction of three factors from 30 observed measures of cognitive style using principal axis factoring and promax rotation. Blanks represent loadings below 0.3.

	Factor 1	Factor 2	Factor 3	Communality	Uniqueness
CS1			0.41	0.22	0.78
CS2		0.62		0.36	0.64
CS3		0.73		0.49	0.51
CS4		0.40		0.29	0.71
CS5		0.74		0.49	0.51
CS6		0.53		0.45	0.55
CS7		0.36	0.35	0.36	0.64
CS8		0.63		0.52	0.48
CS9		0.58		0.41	0.59
CS10		0.71		0.42	0.58
CS11			0.53	0.37	0.63
CS12		0.74		0.45	0.55
CS13		0.49		0.36	0.64
CS14		0.70		0.45	0.55
CS15	-0.63			0.47	0.53
CS16	0.73			0.55	0.45
CS17	0.38			0.18	0.82
CS18	0.54			0.34	0.66
CS19	0.71			0.57	0.43
CS20	0.47			0.25	0.75
CS21	0.65			0.48	0.52
CS22	0.62			0.52	0.48
CS23	-0.84			0.60	0.40
CS24	-0.41			0.27	0.73
CS25	-0.47			0.20	0.80
CS26	-0.70			0.52	0.48
CS27		-0.41	-0.32	0.42	0.58
CS28	0.52	-0.30	0.64	0.54	0.46
CS29	0.39		0.31	0.36	0.64
CS30			0.78	0.56	0.44

Table 2.23. Factor correlation matrix (cognitive style)

	Factor 1	Factor 2	Factor 3
Factor 1	1	0.44	0.14
Factor 2	0.44	1	0.5
Factor 3	0.14	0.5	1

Table 2.24. Standardized ordinal alpha-if-item deleted and item-to-total scale correlations for factors representative of cognitive style

	Ordinal Alpha	Item-Total Correlations
Factor 1		
CS15	0.26	-0.33
CS16	-0.06	0.59
CS17	0.01	0.32
CS18	-0.01	0.40
CS19	-0.11	0.68
CS20	-0.02	0.41
CS21	-0.16	0.75
CS22	-0.03	0.51
CS23	0.28	-0.38
CS24	0.26	-0.37
CS25	0.22	-0.27
CS26	0.31	-0.47
CS29	-0.17	0.71
Factor 2		
CS2	0.80	0.62
CS3	0.80	0.67
CS4	0.82	0.46
CS5	0.80	0.66
CS6	0.80	0.65
CS7	0.81	0.53
CS8	0.80	0.72
CS9	0.80	0.64
CS10	0.80	0.62
CS12	0.80	0.62
CS13	0.81	0.58
CS14	0.80	0.66
CS27	0.88	-0.58
Factor 3		
CS1	0.63	0.48
CS11	0.57	0.60
CS28	0.65	0.47
CS30	0.51	0.69

2.5. Discussion

This section discusses the construct validity and reliability of responses to measures of engineering design task difficulty, task motivation and cognitive style within the context of previous work.

2.5.1. Task difficulty

Factor analysis presented mixed evidence about the reliability and validity of the task difficulty scale. Previous research hypothesized a two-factor model underlying the 14-items scale. The two factors are task structuredness and task complexity (Jonassen, et al., 2008). Extraction of a two-factor model was supported by the EFA. Item reliability analysis suggested poor reliabilities were observed for responses to items loading on the task structuredness factor. Poor reliabilities are expected with a small number of items with high measurement error (uniqueness) loading on the same factor. High reliabilities were observed for responses to items loading on the complexity factor. High reliabilities are expected due to consistency in the description of many items loading on the same factor. Increases in the number of and high quality of items will likely increase the reliability of responses to items loading on the two-factor model. Given the mixed results on item reliabilities, validity of the two-factor model was not expected.

Results suggested that validity of a two-factor model of task difficulty is debatable when a small sample of participants rates an engineering design task. The two-factor model accounted for only 49% of the total explained variance. Contrary to expectations based in literature (Jonassen, et al., 2008), the seven items that represented "structuredness" did not load on the same factor. Two of the seven items cross-loaded on both factors and one item did not load on either factor. Three of the seven items expected to load on the "complexity" factor did not load on either factor. A modest amount of explained variance, loadings contrary to expected in the literature and non-loading items suggest presence of additional factors. In addition, the two-factor model suggests that structuredness and complexity are unrelated since two factors are uncorrelated with each other. Uncorrelated factors make the presence of a higher order factor such as task difficulty implausible. Hence, the existence of a two-factor measurement model is questionable.

2.5.2. Task motivation

Factor analysis presented mixed evidence about the reliability and validity of the 12-items QCM scale. Overall, the measurement model demonstrated weak reliability for a two-factor model of task motivation suggested by the EFA. The two factors were labeled "approach" and "avoidance" as per the approach-avoidance theory of motivation. While participants' responses to items that loaded on the "approach" factor had high internal consistency, responses to items that loaded on the "avoidance" factor showed low internal consistency. The low reliability of responses to "avoidance" may be attributed to items (e.g., TM1 and TM2) loading on the "wrong" factor and/or presence of additional factors as suggested in the literature but not achievable with the current sample size (Wolf, Harrington, Clark, & Miller, 2013) or poor item quality. In the latter case, cross-loading of item TM1 suggests that participants' responses to item TM1 may not necessarily measure only a positive or a negative response to the item. Therefore, item TM1 may not be an appropriate measure to estimate reliability of responses for factor 2. Cross-loading of item TM1 also resulted in sharing of item variance across factors, thereby decreasing the factor loading and lowering reliability estimates when clustered with other items on factor 2. In addition, the negative loading of item TM2 on factor 2 suggests (contrary to literature) the item should be reverse-coded to achieve a higher internal consistency. Given these shortcomings, validity of model was not expected in this study.

Both the CFA and EFA results, however, provided some evidence validity for a two-factor model over a four-factor model of task motivation when few participants (compared to original study) were asked to rate an engineering design task. The CFA results indicated that the observed data does not support the presence of a four-factor model of task motivation underlying the QCM (Fruend, et al., 2011). The EFA results indicated that a two-factor model of task motivation ought to be extracted in spite of the presence of additional factors suggested by a modest explained variance and high uniqueness values. Both results indicated that the original four-factor model does not hold under the conditions (smaller sample size, design task) of this study. Nonetheless, the validity of the two-factor model of task motivation was supported by an alternate theory of motivation. One theory (Elliot & Thrash, 2002) has situated motivation in the context of persons' positive or negative reactions to a task. An observation of the type of items (i.e., a positive or a negative response) that loaded on both factors indicated that similar items, which represent a positive approach or an avoidance approach to a task, collectively load on separate factors. Agreement with "approach/avoidance" theory gives the two-factor measurement model some validity.

2.5.3. Cognitive style

Factor analysis presented mixed results about reliability and validity of the 30 items A-E scale. Previous research (Martinsen, et al., 2011) proposed a three-factor model of cognitive style. The factors were rule-orientation, planning, and novelty-seeking. Consistent with previous work, EFA supported presence of a three-factor model. Reliability of participants' responses to observed measures, however, varied from poor to fair. Poor internal consistency may be due to incorrectly coded items (e.g., factor 1, novelty-seeking) and small number of poorly correlated items (e.g., factor 3, planning). Incorrect (reverse-) coding for factor 1 is evident from presence of both positive and negative loading items on the same factor. Poor correlations between items on factor 3 are supported by presence of low correlations in the inter-item polychoric correlations matrix. Overall, internal consistency may be improved by reversing reverse-coded items, using similar measures, and increased number of items. Given the weak reliability of responses to items on two of the three factors, weak construct validity was expected for the three-factor model.

The three-factor measurement model of cognitive style demonstrated weak construct validity despite a fair model fit in CFA modeling. The three factors were labeled novelty-seeking (factor 1), rules-orientation (factor 2), and planning (factor 3). A weak construct validity can be a result of a non-simple (cross-loading items) factor structure. Cross-loadings result in factor structures that may be uninterpretable because of indistinguishable factors. Considering numerous items in the original model (Martinsen, et al., 2011) load on multiple factors, weak validity of the three-factor model may be attributable to cross-loading items on the cognitive style scale. Results from the EFA supported the presence of a more valid three-factor structure which is different from and simpler (i.e., fewer cross-loadings) than the original factor structure. Low factor correlations (compared to the original model) also suggest a simple structure may increase construct validity.

2.6. Conclusion

Clarifying claims about the conflicting roles of engineering curricula in developing students' abilities to innovate solutions to design problems necessitated development and evaluation of measures of students' interactions with the curricula. The purpose was to examine construct validity and reliability of measures of task difficulty, current achievement motivation and cognitive style for use in research on students' abilities to innovate solutions to engineering design problems. A prospective, survey research design was used to collect data from a sample of engineering students from Texas A&M University. Confirmatory factors analysis (CFA), exploratory factor analysis (EFA), and item analysis were used to determine the construct validity of three measures. Reliabilities of measures were estimated from composite reliability and ordinal alpha values. Fit indices obtained from the CFA did not support a well-fitting two-factor and four-factor model for task difficulty and current achievement motivation, respectively; however, an acceptable three-factor model was achieved for cognitive style. Further analysis, however, indicated that the cognitive style model did not achieve convergent and divergent validity. EFA supported presence of a two-factor model of task difficulty, a two-factor model of current achievement motivation, and a three-factor model of cognitive style. However, the resulting factor structures had issues such as non-loading items, cross-loading items, and poor internal consistency estimates. Measures of task difficulty, current achievement motivation and cognitive style have weak construct validity and response reliability. Additional studies, with a large sample size and improved item quality, should be conducted to verify the conclusions formed through this research and obtain construct valid and reliable measures of task difficulty, current achievement motivation, and cognitive style.

3. PREDICTING THE ROLES OF DOMAIN EXPERTISE, CURRENT ACHIEVEMENT MOTIVATION AND COGNITIVE STYLE IN GENERATING NOVEL SOLUTIONS TO ENGINEERING DESIGN TASKS

3.1 Introduction

Preparing engineering students with abilities to provide innovative solutions to increasingly challenging design problems is essential to their success. Recent research suggests that engineering students are ill-prepared to solve challenges that require them to generate innovate solutions. For example, a study (Lai, Roan, Greenberg & Yang, 2008 and Genco, Holta-Otto & Conner Seepersad, 2012) reported that while both seniors and freshmen produced ideas of similar quality, seniors were less proficient at creating original solutions to ill-defined problems using creative thinking than freshmen. The findings warrant discovery of ways engineering programs can support development of students' abilities to generate innovative solutions to design problems as they advance through the curriculum. Such support would help students become more innovative engineers.

While engineering programs may support development of students' abilities to innovate in multiple ways, this research focuses on how programs can help students develop their abilities to provide innovative solutions to a design task via the development of their creativity-related characteristics using engineering design tasks. Characteristics such as an individual's domain expertise, creativity-relevant skills, and motivation influence creative performance (Amabile, 2013; Jo & Lee, 2012; Martinsen

& Diseth, 2011). This study is unique in its use of a model that accounts for combined roles of domain expertise, creativity-relevant processes and task motivation for predicting novelty of solutions using decision tree analysis.

3.2. Research Purpose and Question

This research determined combinations of engineering students' characteristics that predict novelty of students' solutions to an engineering design task. Students' characteristics considered in this research are Grade Point Average (GPA), university classification, major, familiarity with assigned design task, current achievement motivation and cognitive style. This research was conducted using a combination of the multiple components approaches and the psychometric approaches to creativity, to advance research and practice in engineering education. The research question that was posed in this research is:

> How do engineering students' GPA, classification, major, familiarity with a design task, current achievement motivation and cognitive style combine to predict novelty in their solutions to an engineering design task?

This research furthers engineering education research and practice in three ways. One, it tests Amabile's hypotheses about creativity and verifies relationships outlined among domain expertise, motivation and creativity relevant processes in Amabile's componential theory of creativity (2013), thereby giving strength to evidence for future use of Amabile's theory to frame research studies on creativity in engineering education. Two, it clarifies the importance education researchers can assign to students' characteristics when comparing advantages and disadvantages of different ideation techniques, to determine usability of different idea generation techniques by students. Three, it provides findings about combinations of students' characteristics which support/do not support novelty in students' solutions to design problems. These findings are essential for developing instructional strategies engineering faculty can use to enhance students' abilities to generate innovative solutions to challenging design problems.

3.3. Background

Several approaches can be used to study creativity. The approaches include case studies, psychoanalytic theories, psychometric approaches, sociological and historiometric approaches, multiple components approaches, pragmatic approaches, artificial intelligence approaches, and creative cognition approach (Finke, Ronald, Ward, Smith, 1996). See Finke, et al. (1996) for a descriptive review of approaches to creativity. Of these approaches, a combination of the multiple components and the psychometric approaches is used to study creativity in present research. While the multiple components approach offers the most comprehensive way to examine creativity, the psychometric approaches are popular ways to measure students' characteristics and creativity in educational psychology. Therefore, these approaches are used in present research.

3.3.1. Multiple components approach

Amabile's componential theory of creativity was selected to frame this study. This theory (Amabile, 1996) is well known, comprehensive, and useful for selection of task, student, and outcome characteristics important for studying creativity. The theory describes the relationship between a task and a creative outcome via a description of the creative process and four components and their interactions with the task, the creative process and the creative outcome. A description of the various aspects of the theory is presented in this section.

3.3.1.1. Task

Amabile's theory of creativity poses that the task presented to a person ought to be open-ended, i.e., present the person with an opportunity to find many or no solutions, to activate solution finding. The task can either be self-found or posed to the person by another individual or organization. (Amabile, 2013)

3.3.1.2 Creative process

The creative process in Amabile's theory consists of four sequential steps: problem identification; preparation; response generation; and response validation and communication. Problem identification refers to presentation of a problem or task to a person. Preparation refers to accessing stored domain knowledge relevant or gathering the knowledge needed to solve the problem or task. Response generation refers to exploring both memory and environment to generate possible solutions to the problem or task. Response validation and communication refers to testing feasibility of responses using relevant criterion and domain knowledge. The four steps in the creative process lead to a successful, unsuccessful or semi-successful outcome. The semi-successful or the unsuccessful outcomes can lead the person back to any one of the previous steps to produce a successful product. (Amabile, 2013)

3.3.1.3. Creative outcome

In Amabile's theory, creativity of an outcome lies on a continuum that ranges from low to high. In addition, varied levels of creativity can be displayed even within the same domain because of interaction between the four components of creativity. The outcome is measured in terms of novelty and appropriateness (i.e., usefulness). While novelty of solutions is determined during the response generation step, appropriateness is determined during the response validation and communication step in the creative process. (Amabile, 2013)

3.3.1.4. Components influencing creative process and outcomes

The four components that influence the creative process and hence the creative outcomes are domain-relevant skills, creativity-relevant processes, task motivation, and environment. According to Amabile (2013, p. 1), "domain relevant skills include knowledge, expertise, technical. skills, intelligence, and talent in the particular domain…" and "creativity-relevant processes include cognitive style and personality characteristics that are conducive to independence, risk-tasking, and taking new perspectives on problems" and "disciplined work style and skills in generating ideas" (p. 2). Task motivation is "the motivation to undertake a task or solve a problem because it is interesting, involving, personally challenging, or satisfying" (p. 2). Environment refers to social and other factors (e.g., extrinsic motivators such as rewards or punishment) outside the individual. Of the four components, domain-relevant skills, creativity-relevant skills and task motivation are persons' characteristics.

3.3.1.5. Relationships among multiple components influencing creative process and outcomes

Amabile (2013) illustrates direct and primary influences of the four components of creativity on each other and the creative process in a simplified model. According to this illustration, a person's social environment influences his or her task motivation. Task motivation in turn influences problem or task identification, response generation, learning of domain-specific skills, and/or setting or breaking of creativity-relevant processes. The domain-relevant skills influence both the preparation and the response validation and communication steps of the creative process, and the creativity-relevant processes influence a person's response generation. The process outcome (success, progress, or failure) can increase or decrease a person's task motivation.

3.3.2. Psychometric approach

The relationships among the multiple components of Amabile's theory were examined using the psychometric approach to creativity. The psychometric approach offered a way to measure multiple components of creativity directly and with ease using a survey. Measures of the components and the survey are described in detail in the methods section. This research study tested its hypotheses with observations obtained from the survey.

3.3.3. Hypothesis

Amabile's (1996) componential theory of creativity offers eight hypotheses about how domain-relevant skills, creativity-relevant processes, and task motivation combine to form a creative outcome. According to the theory (2013, p. 1), "creativity [of an outcome] should be highest when an intrinsical.ly motivated person with high domain expertise and high skill in creative thinking works [on a task] in an environment high in support for creativity". Moreover, and without exception, high to moderate creativity outcomes should be obtainable when at least two of the three personal characteristics combine at high levels. Some novelty, however, should al.so be obtainable in low creativity solutions when an individual. is highly motivated to solve the task. (Amabile, 1996) The present study tested these hypotheses using a decision tree analysis with a sample of undergraduate engineering students.

3.3.4. Previous research

Previous research supported roles of domain-relevant skills, creativity-relevant processes, and task motivation in creative outcomes (Amabile, 1996); however, empirical research that examines their combined roles on creativity is sparse. Example studies include Martinsen and Kaufmann (2000) and Jo and Lee (2012). Martinsen, et al. (2000), who studied effects of task motivation and A-E cognitive style on problem-solving performance, found that highly motivated individuals with explorer cognitive styles underperformed individuals of the same motivation but with assimilator cognitive styles when working on insight problems. Jo, et al. (2012) modeled links among task complexity, intrinsic motivation, organizational trust, and creativity of individuals working in Korean ICT companies and found that both motivation and organizational. trust had positive influences on creativity. In their study, intrinsic motivation had the most influence of all independent variables on individual creativity. The researcher did not find previous research that tested the combined roles of domain-relevant skills, creativity-relevant skills, and motivation with a sample of undergraduate engineering students using a decision tree analysis. Use of the decision tree analysis helps test hypotheses of creativity offered in Amabile (1996) for this population without the limitations of regression analysis. In addition, it helps identify ranges of values of characteristics for which the hypotheses hold/do not hold. Further, the decision tree analysis helps recognize significant ways engineering students' characteristics combine to predict creativity of solutions to an engineering design task. The significant combinations offer preliminary hypotheses, which researchers can test against a control group, to develop instructional strategies to support novelty in engineering students' solutions to a similar design task.

3.4 Methods

Decision tree analysis was used to determine how engineering students' GPA, classification, major, familiarity with the design task, current achievement motivation and cognitive style combine to predict novelty of students' solutions to an assigned design task. Use of decision tree analysis is appropriate when researchers desire to predict group membership to a categorical variable (i.e., dependent variable) based on predictor variables (i.e., independent variables) which are categorical and/or continuous and data violates assumptions of other commonly used group membership methods (e.g., logistic regression) (Maindonald & Braun, 2013). The dependent variable in this research was novelty of solutions (binary, categorical). The independent variables were GPA (continuous), classification (categorical), major (categorical), familiarity with the design task (categorical), current achievement motivation (continuous) and cognitive style (continuous). The hypotheses proposed in the introduction were tested using measurements of dependent and independent variables with a sample from the target population. Ideally, the results from a decision tree analysis are cross-validated with a different sample from the same population. However, the cross-validation was limited in this research due to lack of access to a large sample size.

3.4.1. Target population

The target population for this research study consisted of all undergraduate engineering students enrolled at a large, research extensive, public university in the southern United States during the 2015-2016 academic year. The average population size was approximately 11263 students. Approximately 21% were females and 78% were males. The population consisted of freshmen (18% - 27%), sophomores (21%), juniors (19% - 22%) and seniors (32% - 38%) over the two semesters. The ranges in classification estimates reflect variability in enrollment over the two academic semesters. The approximate number of students affiliated with each department is presented in Table 3.1. (Texas A&M University – College Station, 2017) The mean Grade Point Average (GPA) of students in the population is not accessible without institutional. permissions and therefore unknown for this research; however, it is presumed to fall between 0.0 and 4.0 because the university computes students' grade point average on a four-point scale.

The target population for this study was selected out of interest from both the US government and industry and researcher's interest and convenience. Both the US government (US Department of Commerce, 2012) and industry have expressed interest in preparing engineering undergraduates with abilities to provide innovative solutions to challenging design problems encountered in the workplaces. Findings derived from research on this population addressed the needs expressed by both the government and industry. Further, present researcher identified needs in the literature to study this population. In addition, the target population was easily accessible via e-mails through the existing network of colleagues, in-person recruitment and experiment visits required of participants.

Table 3.1. Departmental affiliation and approximate percentage of students in the target population during the 2015-2016 academic year

Department affiliation	Students (%)
Aerospace engineering	4
Biological and agricultural engineering	Unknown
Biomedical engineering	2
Chemical engineering	5
Civil engineering	6
College of engineering	28 - 31
Computer science and engineering	8
Electrical and computer engineering	7
Engineering technology and industrial distribution	12 - 13
Industrial and systems engineering	7
Mechanical engineering	9
Nuclear engineering	2
Ocean engineering	1
Petroleum engineering	5

3.4.2. Recruitment and selection

Multiple tactics were used to recruit participants for this research study. First, engineering students of freshmen, sophomore, junior or senior classification were invited to participate in the study via the university bulk-e-mail system. Second, the research study was advertised to students via e-mails through their professors and presentation during class. Third, the researcher made visits to engineering classrooms, primarily capstone design in mechanical engineering, to recruit participants for the research study. The capstone design classrooms were chosen strategical.ly for their high enrollment of students with senior classification.

Students self-selected to participate in the research study using an online study invite form. Use of different recruitment tactics resulted in a participation interest rate of approximately 5 % (~ 600 students). Of the 5% who expressed interest in participating in this research, approximately 60 % visited the research site to participate in the study. Students who consented to participate at the research site constituted the study sample.

3.4.3. Participants

The study sample consisted of 361 undergraduate engineering students. Characteristics of the sample are presented in Table 3.2. As seen from Table 3.2, the sample consists of more males than females. This trend is consistent with the trend about gender observed in the target population. Freshmen and sophomores comprise the majority of participants in the sample. Notably, the two lower-level university classification groups were more amenable to participation in research than juniors and seniors in the population. The majority of participants in the sample are al.so affiliated with either the college of engineering or mechanical engineering. Those who were affiliated with the college of engineering are freshmen who had not yet chosen a major. A high number of mechanical engineering participants resulted from the focused recruitment. A mean GPA of 3.2 is reported for the sample. A mode GPA of 4.0 in the sample suggests that most students who participated in this research are high-achieving students.

Table 3.2. Sample characteristics. Total number of participants is 361.

	N = 361	
Category	n	%
Gender		
Female	143	39.6
Male	217	60.1
Unknown	1	0.3
Classification		
Freshman	114	31.6
Sophomore	104	28.8
Junior	45	12.5
Senior	98	27.1
Department		
Aerospace engineering	15	4.2
Biological and agricultural engineering	1	0.3
Biomedical engineering	-	-
Chemical engineering	18	5.0
Civil engineering	11	3.0
College of engineering	73	20.2
Computer science and engineering	28	7.8
Electrical and computer engineering	29	8.0
Engineering technology and industrial distribution	15	4.2
Industrial and systems engineering	10	2.8

Table 3.2. Continued

Category	N = 361 n	%
Mechanical engineering	143	39.6
Nuclear engineering	11	3.0
Ocean engineering	-	-
Petroleum engineering	7	1.9
Familiarity with design task		
Not at all	197	54.6
Very little	131	36.3
Fairly well	21	5.8
Quite well	6	1.7
Perfectly	2	0.6
Not reported	4	1.1
Grade Point Average (GPA)		
Reported (on 4.0 scale)	303	83.9
Not reported	58	16.1
Mean (standard deviation)	3.2 (0.5)	
Median	3.3	
Mode	4.0	
Range	0.8 – 4.0	

3.4.4. Design task

Aligned with assumptions presented in Amabile's framework, a design task was posed to the participants to trigger their creative processes. Specifically, the researcher assigned a "mixed wasted [sic] collection" design task to participants. This task required participants to develop concepts to separate paper and plastic from a mixed waste collection and was presented as such:

> One of the different systems used for curbside recycling is "mixed wasted collection" in which all recyclates are collected mixed and the desired material. is

> then sorted out at a sorting facility. One difficult sorting task is separating paper and plastic, which is usually done by hand. Develop concepts that will enable removing paper or plastic from the mixed collection. (Cheong, Chiu, & Shu, 2010)

This task was presented in text format because this format is typical of the format presented to engineering students in cornerstone and capstone courses (personal experience). In addition, the design task is open-ended and therefore gives students an opportunity to find no or many solutions.

While other types of tasks may be posed, this research focused on a design task because instructor-assigned design tasks form the crux of student experience in in engineering. The researcher chose to use the mixed waste collection task because of its successful use in previous research on design ideation. In addition, this task was expected to invoke large amounts of variations in participants' responses. The large amounts of variations are important for distinguishing the extent to which students' characteristics predict novelty of their solutions. Given these characteristics, the researcher used the design task to examine how students' characteristics combined to predict novelty of solutions to the task in an academic environment with a survey.

3.4.5. Students' characteristics

Amabile's theory highlighted domain-relevant skills, creativity-relevant processes and task motivation as the types of student characteristics that influence the creative process and the outcome. Influences of a subset of the three characteristics were considered in this research due to research purpose and constraints. Of the domain-relevant skills, only domain expertise was measured in this research. Other sub-components were not measured due to time constraints and concerns about participant fatigue and loss of interest in a lengthy study. The latter concerns can influence reliability of measurements and therefore affect the overall conclusions derived from this research. Domain expertise was estimated from an individual's Grade Point Average (GPA), university classification, discipline, and familiarity with a design task. GPA is defined as the number of grade points earned divided by number of credit hours attempted (Registrar's office, 2014). University classification is defined as the number of attempted credit hours (Student Rule 13, 2014), and discipline is defined as major affiliation. While GPA has been reported not to influence creativity in previous research in engineering (Nazzal, 2015), the finding was re-tested in this research. Class, major and familiarity with task have been reported to influence creativity (Genco, et al., 2012; Nazzal, 2015; Amabile, 1996). Students self-reported their GPA, classification, discipline and familiarity with the assigned design task on the survey.

Of the creativity-relevant processes, only cognitive style was measured in current research. Cognitive style, which is defined as individual differences in orientation towards different problem-solving strategies used to solve a problem (Martinsen & Kaufmann, 2011) in this research, correlates with personality traits and explains the variance in outcomes beyond the variance explained by personality traits (Martinsen & Kaufmann, 2011). Cognitive style was measured using a revised 30 item Assimilator-Explorer (A-E) inventory that and has its basis in the A-E cognitive style theory. The A-E theory positions students on a style continuum that ranges from rule-conforming (left-end, assimilators) to novelty-seeking (right-end, explorers) behaviors of problem solving. A three-factor model was identified to describe cognitive style, where the factors explain students' preferences for rules, planning and novelty seeking behaviors during problem-solving. (Martinsen et al., 2011) The A-E inventory was established as valid and reliable in related research (Rathore, unpublished work). Therefore, the items on the A-E inventory were used to measure students' cognitive style on the survey.

Task motivation was measured as Current Achievement Motivation (CAM). CAM is defined as student's achievement on a task as mitigated by task characteristics (Fruend, Kuhn, & Holling, 2011). CAM has four facets. The facets are anxiety, challenge, interest and probability of success. The four facets represent intrinsic motivations. Fruend, et al. (2011) argued that interest (an indicator of current achievement motivation) is a significant predictor of creativity. CAM was measured using a short Questionnaire on Current Motivation (QCM). The QCM is composed of a 12 item that was reported as valid and reliable in related research. (Fruend, et al., 2011) Therefore, items from the QCM were used to measure students' motivation on the survey.

3.4.6. Environment

While present research considered a subset of components of domain expertise, creative thinking, and motivation, it did not consider the environment directly. Physical environment either was outside of the researcher's control or presumed fixed when students worked in the same physical space. In addition, previous research demonstrated that the physical environment has a relatively smaller impact on creativity when compared to the social environment (Dul, Ceylon & Jaspers, 2011). Therefore, this research neglected the measurement of the effects of physical environment on creativity. In addition, this research did not consider the social environment directly due to research purpose and time constraints; however, since social environment of a person influences his or her task motivation (Amabile, 2013) the effects of social environment were presumed reflected in the task motivation measurement. Monetary reward, regardless of success or failure, was held constant in this research.

3.4.7. Creative outcome

Though Amabile's theory of creativity describes the creative outcome in terms of novelty and usefulness, only novelty - defined as something new/original (Sarkar et al., 2011) - is chosen to represent students' abilities to provide innovative solutions. This is because recent literature (Lai, et al., 2008; Genco, et al., 2012) suggested that originality of student-generated solutions diminishes as undergraduate students advance through the engineering curriculum. Novelty was estimated as low or high based on the rarity of solutions in the sample. The rarer the idea, the more novel it is. This assumption is consistent with the assumption of creativity lying on a continuum that ranges from low to high in Amabile's theory of creativity (Amabile, 2013).

3.4.8. Data collection

Data was collected from participants using a prospective, survey research design approach after obtaining permissions from the university's Institutional. Review Board. Participants completed an online survey after consenting to participate in this research. The survey consisted of four forced-choice categorical items, one forced-choice open-ended item, two forced-choice Likert-scales, and one forced-choice brainstorming essay item. Categorical and open-ended items captured demographics variables such as a student's gender (categorical), university classification (categorical), department affiliation (categorical), familiarity with the design task (categorical) and GPA (open-ended). The two Likert-scales were measures of current achievement motivation and cognitive style, respectively. The scales and their validities and reliabilities are described in detail in (Rathore, unpublished work). Participants rated their perceptions of motivation to engage with and general approach to problem-solving in engineering for the assigned design task on the two Likert-scales. The brainstorming essay item instructed participants to generate as many solutions to the design task as possible in 10-minutes. Participants sketched their ideas on paper and provided textual descriptions of their ideas in the essay item. Participants received monetary compensation for completing the online survey.

3.4.9. Data analysis

Data was analyzed in R (R Core Team, 2017) using decision tree analysis to predict novelty of solutions to a design task based on students' GPA, classification, and major, familiarity with the task, current achievement motivation, and cognitive style. Prior to running the decision tree analysis, the raw data was screened for missing values. Missing values, where possible, were replaced with a typical variable response. For example, null GPA values were replaced with the median GPA. Where a statistical decision could not be made about missing values (e.g., familiarity with task or novelty), cases were eliminated from further analysis.

Further, categorical independent variables were re-coded by collapsing categories to achieve an adequate sample size (by decreasing number of predictors) and a non-zero and near thirty-cell frequency count. For example, the four categories of classification were recoded to two categories. Participants who were classified as freshmen or sophomores were re-classified to the “lower division” category. Participants who were classified as juniors or seniors were re-classified to the “upper division” category. Participants who may have similar disciplinary knowledge were re-assigned to the same major category. Participants’ familiarity with the design task was recoded to familiar or not familiar. The coding key is presented in Table 3.3.

Data recoding was followed by computations of participants’ scores on the questionnaire of current achievement motivation (QCM) and the cognitive style inventory. Exploratory factor analyses (EFA) was first run in R (version) for both scales to determine their respective factor structures. The EFA procedures are described in detail in (Rathore, unpublished work). Factor scores for each scale were then estimated using the tenBerge method (Revelle, 2017). Descriptive statistics were obtained for continuous predictors.

Novelty level of participants' solutions to the design task was assigned based on an analysis of qualitative responses to the brainstorming essay item on the survey. Qualitative responses were first coded into bins with similar ideas. For example, an idea that hinged on separating paper and plastic via optical detection of material properties

Table 3.3. Coding key used to re-classify categorical independent variables for decision tree analysis

New Code Description	Old Code Description
Classification	
Lower division	Freshman
	Sophomore
Upper division	Junior
	Senior
Department	
Major 1	Aerospace engineering (AERO)
	Civil engineering (CVEN)
	Mechanical engineering (MEEN)
Major 2	Biological and agricultural engineering (BAEN)
	Biomedical engineering (BMEN)
	Chemical engineering (CHEN)
	Nuclear engineering (NUEN)
	Ocean engineering (OCEN)
	Petroleum engineering (PETE)
Major 3	Computer science and engineering (CSEN)
	Electrical and computer engineering (ECEN)
Major 4	Engineering technology and industrial distribution (ETID)
	Industrial and systems engineering (ISEN)
Major 5 (Undeclared)	College of engineering (CLEN)
Familiarity with design task	
Not familiar	Not at all
Familiar	Very little
	Fairly well
	Quite well
	Perfectly

was put in one bin. An idea that suggested separating paper and plastic using the buoyancy principle was put in another bin. Once all (516) ideas were coded into their respective bins (total. bins: 107), the number of ideas per bin was computed for each bin.

The bins were then assigned a "novelty" grade (1-20) based on the number of ideas in the bin. The bin with the highest number of ideas (e.g., 44 ideas) was assigned the lowest grade (e.g., grade = 1). Higher the number of ideas, lower the grade assigned. All bins with the same number of ideas and all ideas inside the same bin were assigned the same grade. After assignment of grades to bins/ideas, an average novelty score of ideas was computed for each participant. Participants' scores were categorized next into either low novelty or high novelty depending on their location on the novelty grade. Scores lower than or equal to 10 were coded as low novelty, and scores higher than 10 were coded as high novelty.

The decision tree analysis was first run in R using the recursive partitioning (rpart) package at its default values (Therneau, Atkinson & Ripley, 2017). The rpart algorithm combines tree building with cross-validation to generate the “best” tree. The full tree was built recursively with predictors that best split the data into two groups until no improvement was made or a minimum sample size was achieved by the split (i.e., low prediction error). The resultant tree was then pruned back using a complexity value with the least amount of 10-fold cross-validation error. The pruned tree is a parsimonious model that avoids overfitting and improves the model’s predictive ability. Predictor importance was computed. The randomForest package – a random bootstrapping algorithm – was al.so run to determine if bootstrapping improves the predictive abilities of the model (Liaw & Wiener, 2002). Decisions trees, complexity and cross-validation error tables, importance terms and confusion matrices computed from the rpart and randomForest packages are presented in the results section.

3.5. Results

A summary of the results from the decision tree analysis is presented in tandem with supporting evidence from the descriptive analysis in this section.

The full tree obtained from the rpart package indicates that GPA, major, current achievement motivation and cognitive style are the only characteristics that combine to predict students' abilities to generate novel solutions. Participants' university classification and familiarity with the design task did not enter the model. The full tree is presented in Figure 3.1. As seen in Figure 3.1, the significant predictors in order from most to least significant are: challenge, anxiety, GPA, novelty seeking orientation, interest, major (c ≠ major 2; e ≠ major 4), probability of success, and rules orientation.

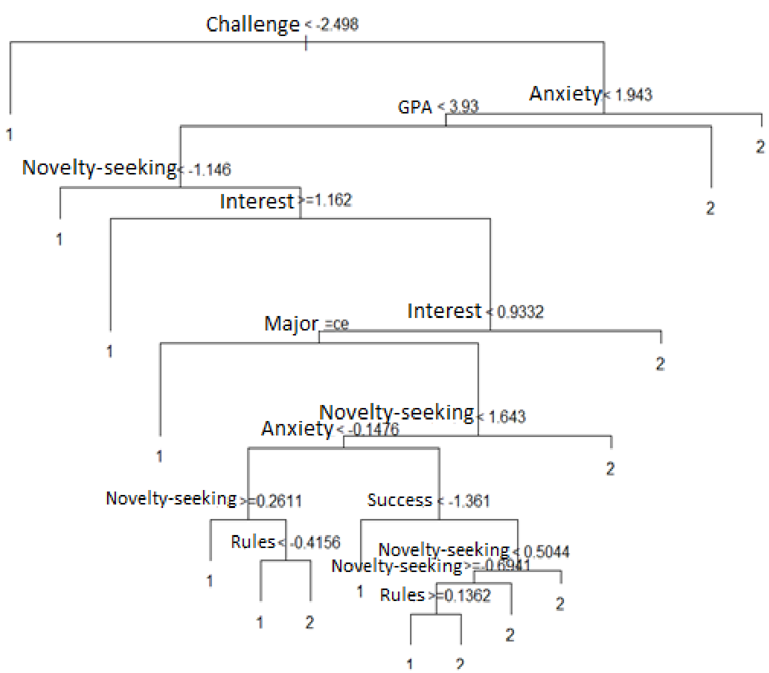

Figure 3.1. Full decision tree obtained from rpart package. Predictors: challenge, anxiety, GPA, novelty-seeking orientation, interest, major (c = major 2, e = major 4), probability of success, and rules. Outcome: 1 = low novelty, 2 = high novelty

The decision tree contains eight combinations that predict high novelty solutions and eight combinations that predict conventional solutions. Individual combinations are achieved using the splitting variable rules (e.g., challenge <-2.50). When a splitting variable rule is met, the outcome to the left is observed. For example, high novelty solutions are observed when challenge and anxiety combine in the following way (challenge > -2.50) AND (anxiety > 1.94). A conventional solution is observed when participants' score on challenge is less than 2.50. The full decision tree al.so suggests interaction variables in the model. Anxiety interacts with GPA, novelty-seeking orientation, interest and major. In addition, novelty-seeking orientation interacts with itself, major, interest, anxiety and probability of success.

However, because the full decision tree was complex, this tree was pruned using the complexity parameter with the lowest cross validation error and good predictive accuracy. Values of complexity parameters and cross-validation errors are presented in Table 3.4. As seen from Table 3.4, the full tree achieves lowest cross-validation error of 32 % at the seventh split. Cross-validation error is root node error times relative error.

Table 3.4. Complexity parameters (CP), number of splits (nsplit), relative error (rel error), cross-validation error (xerror), and standard error (xstd) suggesting pruning of full tree at CP = 0.04

	CP	nsplit	rel error	xerror	xstd
1	0.0660	0	1	1	0.0695
2	0.0472	1	0.9340	1.1132	0.0692
3	0.0425	5	0.7453	1.0377	0.0695
4	0.0400	7	0.6604	1.0377	0.0695

Root node error: 106/217 = 0.48848

The pruned decision tree obtained from the rpart package is presented in Figure 3. 2. As seen in Figure 3.2, significant predictors of novel solutions are challenge, anxiety, GPA, novelty seeking, interest, and major. The decreasing order of relative importance of predictors is interest, challenge, anxiety, GPA, novelty-seeking orientation, major, and probability of success.

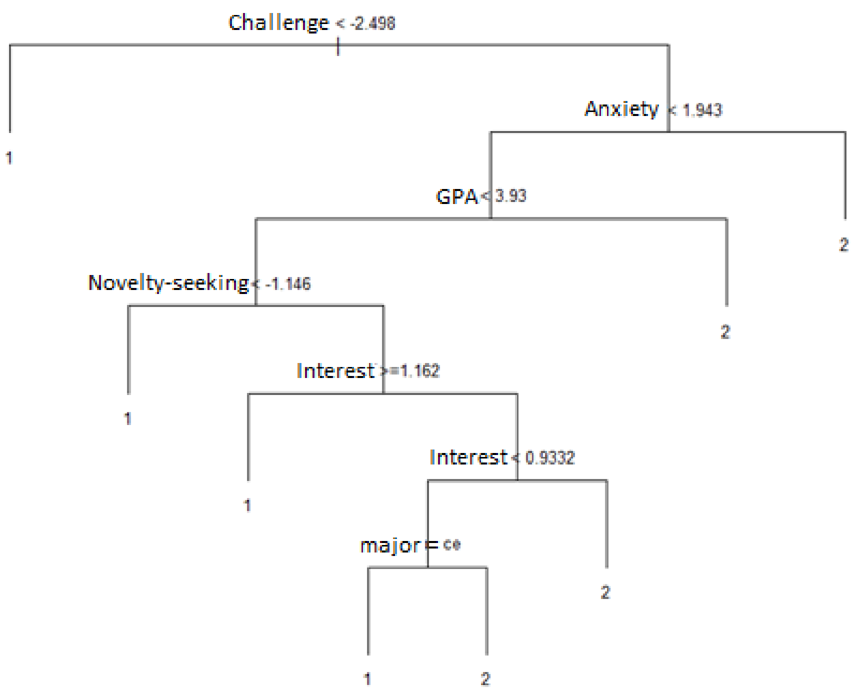

Figure 3.2. Pruned decision tree. Predictors: challenge, anxiety, GPA, novelty-seeking orientation, interest, major (c = major 2, e = major 4). Outcome: 1 = low novelty, 2 = high novelty

The pruned decision tree is reliable in predicting novelty of solutions based on significant characteristics of students. The confusion matrix for the pruned decision tree is presented in Table 3.5. As seen from Table 3.5, the misclassification error for a low novelty solution as a high novelty solution is 25%. The error for misclassifying a high novelty solution as a low novelty solution is 36%. Overall, the pruned tree predicts a high novelty solution more accurately than a low novelty solution. Further improvement to prediction was not possible without overfitting the original model. As seen from Table 3.6, prediction capabilities of the decision tree deteriorate when randomForest – a random bootstrapping algorithm - is applied to the model. Therefore, the pruned tree obtained from the rpart package is sufficient for interpretation.

Table 3.5. Actual (row) vs. predicted (column) values with predictor errors for the pruned tree

	1	2	class.error
1	54	18	0.25
2	52	93	0.359

Table 3.6. Confusion matrix from the randomForest algorithm

	1	2	class.error
1	46	60	0.566038
2	52	59	0.468469

OOB estimate of error rate: 51.61%

Figure 3.3 and Table 3.7 present results from the descriptive analysis of significant predictors from the pruned tree. As seen from Figure 3.3, the majority (77.88%) of the participants were from aerospace engineering, civil engineering or mechanical engineering. Approximately, 34% of the participants were undeclared majors. About 26% of the participants were from computer science and engineering and electrical and computer engineering. Seventeen percent were from biological and agricultural engineering, biomedical engineering, chemical engineering, nuclear engineering, ocean engineering or petroleum engineering. The least number of participants (11.52%) were from engineering technology and industrial distribution and industrial. and systems engineering.

Participants' GPA ranged from 0.80 to 4.00. As seen in Figure 3.3 and Table 3.7, the distribution of GPA was left-skewed and had a high splitting variable value of 3.93. The frequency analysis indicated that the majority of the participants were high-achieving students; however, they fell below the splitting threshold value of GPA.

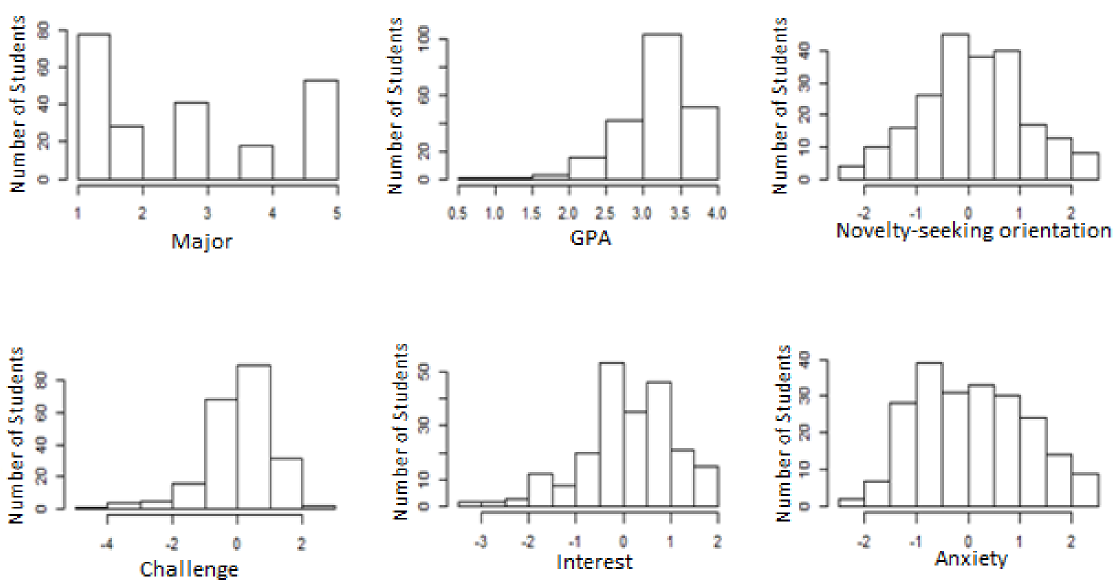

Figure 3.3. Number of students versus rating on predictor variables. Predictors (top left – bottom right): major, GPA, novelty-seeking orientation, rules orientation, interest, anxiety, probability of success, and challenge

An almost normal distribution was observed for novelty-seeking orientation and anxiety. Scores for the novelty-seeking orientation ranged from -2.29 to 2.49 with a splitting threshold value of -1.15. As seen in Figure 3.3, the majority of scores fell above this splitting threshold. The relatively low threshold value on the range suggested that majority of participants seek novel ways to solve design tasks. Few participants experienced high anxiety relative to the threshold value of anxiety.

Table 3.7. Descriptive statistics for continuous predictors in the pruned decision tree

Predictor	Minimum	Maximum	Thresholds
Challenge	-4.30	2.20	-2.45
Anxiety	-2.09	2.49	1.94
GPA	0.80	4.00	3.93
Interest	-3.49	1.95	0.93, 1.16
Novelty-seeking	-2.29	2.49	-1.15

A left-skewed distribution was observed for both challenge and interest. As seen from Figure 3.3 and Table 3.7, the majority of participants scored above the threshold value of challenge. In other words, very few participants found the task not challenging enough to generate novel solutions. The majority of participants also fell outside the small splitting threshold range (0.93, 1.16) of interest.

The pruned decision tree offers eight combinations of students' characteristics that predict novelty of students' solutions to a design task. Of the eight, four combinations predict conventional solutions. The remaining four combinations predict novel solutions. All eight combinations are described. The description of predictors as "low", "medium" and "high" is relative to their respective threshold values. Threshold values of predictors are rounded up to two decimal places.

Conventional solutions were observed under the following rules:

a. (Challenge < -2.50). Conventional solutions were observed when participants perceived the assigned design task to be less challenging than the threshold value of -2.50.

b. (Challenge > -2.50) and (Anxiety < 1.94) and (GPA < 3.93) and (Novelty-seeking orientation < -1.15). Conventional solutions were observed when low achieving participants of low novelty-seeking orientation worked on the design task they felt low anxiety for and found to be highly challenging.

c. (Challenge > -2.50) and (Anxiety < 1.94) and (GPA < 3.93) and (Novelty-seeking orientation < -1.15) and (Interest ≥ 1.16). Conventional solutions were observed when low-achieving participants of low novelty-seeking orientation worked with high interest and low anxiety on what they perceived to be a highly challenging design task.

d. (Challenge > -2.50) and (Anxiety < 1.94) and (GPA < 3.93) and (Novelty-seeking orientation < -1.15) and (1.16 ≤ Interest < 0.93) and (major = c or e). Conventional solutions were observed when low-achieving participants of low novelty-seeking orientation worked with low or high interest and low anxiety on what they perceived to be a highly challenging design task. Participants who ideated conventional solutions were from biological and agricultural engineering, biomedical engineering, chemical engineering, engineering technology and industrial and industrial distribution, industrial and systems engineering, nuclear engineering, ocean engineering or petroleum engineering.

Novel solutions were observed under the following rules:

a. (Challenge > -2.50) and (Anxiety > 1.94). Novel solutions were observed when participants worked on a highly challenging design task while feeling high anxiety towards the task.

b. (Challenge >-2.50) and (Anxiety < 1.94) and (GPA > 3.93). Novel solutions were observed when high-achieving participants worked on a highly challenging design task with low anxiety.

c. (Challenge > -2.50) and (Anxiety < 1.94) and (GPA < 3.93) and (Novelty-seeking orientation > -1.15) and (0.93 < Interest ≤ 1.16). Novel solutions were observed when low-achieving participants of high novelty-seeking orientation worked on a highly challenging design task with medium interest and low anxiety.

d. (Challenge > -2.50) and (Anxiety < 1.94) and (GPA < 3.93) and (Novelty-seeking orientation > -1.15) and (0.93 < Interest ≤ 1.16) and (major ≠ c or e). Novel solutions were observed when low achieving participants of high novelty-seeking orientation worked on a medium interest, highly challenging design task with low anxiety. Participants who ideated novel solutions were from aerospace engineering, civil engineering, computer science and engineering, electrical and computer engineering, mechanical engineering or undeclared majors.

3.6. Discussion

This study examined how engineering students' GPA, classification, major, familiarity with a design task, current achievement motivation and cognitive style combine to predict novelty of their solutions to an engineering design task using the decision tree analysis. The pruned tree offered eight combinations (see results section) to predict novelty of solutions. Consistent with Amabile's componential theory of creativity (2013), facets of domain-relevant skills, creativity-relevant processes and motivation combine to influence creative outcomes in this research. Challenge (facet of motivation), anxiety (facet of motivation), GPA (estimate of domain skills), novelty-seeking orientation (facet of creativity-relevant process), interest (facet of motivation), and major (estimate of domain skills) were identified as significant predictors of novelty. With the exception of GPA (e.g., Nazzal, 2015), significance of anxiety (Rosenblum, Treffinger, Feldhusen, 1970), novelty-seeking orientation (Martinsen, et al., 2011), and interest (Fruend, et al., 2011) for predicting novelty is consistent with previous research. However, contrary to expectations (Genco, et al., 2011; Amabile, 1996) but consistent with other research (Nazzal, 2015; Rathore, unpublished), university classification and familiarity with design task were not significant predictors of novelty. It is possible classification and familiarity with task did not contain sufficient information about students' domain-relevant skills relative to GPA to separate participants into different groups. Therefore, the two predictors did not appear in the model. Additional studies, with different design tasks and a large sample size, should be run to test the stability of splitting variables and their thresholds.

While the researcher could not verify the hypotheses offered by Amabile (2013) due to methodological limitations, predictions about combinations for novel solutions found in this research were consistent with Amabile's projections. For example, as per Amabile's theory, novelty is obtainable when an individual is highly motivated to solve a task. Combination "a" under "novel solutions" demonstrated that novel solutions were observed when participants felt *high* anxiety towards the design task they found to be *highly* challenging; challenge and anxiety are two facets of participants' achievement motivation. Novelty is also obtainable when at least two of the three components of creativity combine at high levels (Amabile, 2013). Combinations "b" and "c," under "novel solutions" demonstrated that novel solutions were observed when participants of either *high* GPA or *high* novelty-seeking orientation worked on what they perceived to be a *highly* challenging design task. GPA and novelty-seeking orientation are facets of domain-relevant skills and creativity-relevant processes, respectively. As seen from combinations "a-d" under "conventional solutions," novel solutions were not obtainable when none or only one of the components of creativity were favorable to ideating novel solutions. Moreover, according to Amabile's theory (2013), novelty is also obtainable when all three components of creativity combine at high levels. This hypothesis was supported by combination "d" under "novel solutions" where novel solutions were observed for participants of *high* novelty-seeking orientation working on *highly* challenging and medium interest design task using disciplinary expertise. Consistency of these findings with Amabile's theory provides evidence for use of her theory in engineering education research.

Further, findings from the decision tree provide insights about control variables for design education research. The decision tree analysis indicated that students' characteristics such as challenge, anxiety, GPA, novelty-seeking orientation, interest and major are significant primary splitters/predictors of novelty. However, these findings do not suggest that variables that were not selected as primary splitters in the decision tree are insignificant predictors of novelty. It is possible that unimportant variables are secondary splitters (containing same information). It is also possible that a small sample size of various groups rendered significant variables unimportant in present analysis. Therefore, research studies must continue to treat students' characteristics from this study as controls in design education studies. Uncontrolled presence of students' characteristics in design studies may influence findings about advantages of idea generation methods.

Last, findings offer hypotheses that may be tested to develop instructional strategies to support novelty of solutions to a similar design task. For example, present research found conventional solutions were observed when few of the participants found the design task less challenging than the threshold value of challenge. Future research can test if novel solutions are observed when the same participants are assigned a more challenging design task (e.g., separate paper, plastic, and glass) than the assigned design task. Conventional solutions were also observed for the few low achievement participants who felt low anxiety towards a challenging task; however, they fell below the threshold value of novelty-seeking orientation. Future research can test if novel solutions are observed when the same participants are given a repertoire of strategies that develop their novelty-seeking orientation. Further, present research found that novel solutions were observed when participants' interest was held at an optimum level and/or they had the necessary disciplinary knowledge to solve the design task. Future research can explore instructional strategies to engage student interest and/or increase disciplinary knowledge to determine if novel solutions are observed for the conventional participants under instructional interventions.

3.7. Conclusion

Fostering students' abilities to develop innovative solutions to challenging engineering design tasks warranted clarification of roles of students' characteristics on their abilities to generate innovative solutions. The present study determined combinations of engineering students' characteristics such as Grade Point Average (GPA), classification, major, task familiarity, current achievement motivation, and cognitive style that predict novelty of their solutions to an engineering design task. A prospective, survey research design was used to collect data with a sample of engineering students. Decision tree analysis was used to determine combinations of students' characteristics that should be explored to promote novelty in students' solutions. GPA, major, current achievement motivation (facets: challenge, anxiety, interest, probability of success), and cognitive style (facets: novelty-seeking orientation, rules orientation) are significant predictors of novelty. Decision tree suggested four combinations that predict high novelty: (challenge > -2.498) and (anxiety > 1.943); (challenge >-2.498) and (anxiety < 1.943) and (GPA > 3.93); (challenge > -2.498) and (anxiety < 1.943) and (GPA < 3.93) and (novelty-seeking orientation > -1.146) and

($0.9332 < \text{interest} \leq 1.162$); ($\text{challenge} > -2.498$) and ($\text{anxiety} < 1.943$) and ($\text{GPA} < 3.93$) and ($\text{novelty-seeking orientation} > -1.146$) and ($\text{interest} < 0.9332$) and ($\text{major} \neq$ c or e). Findings are consistent with Amabile's theory of creativity, provide insights into control variables for design ideation studies, and offer hypotheses to develop instructional strategies to promote novelty in students' solutions to design tasks. Stability of primary splitting (i.e., predictor) variables and their threshold values should, however, be verified in future studies using different design tasks and a large sample size to confirm findings from present study.

4. ESTIMATING RELATIONSHIPS OF ENGINEERING DESIGN TASK STRUCTUREDNESS AND COMPLEXITY TO NOVELTY OF SOLUTIONS USING STRUCTURAL EQUATION MODELING

4.1. Introduction

Helping undergraduate engineering students to develop their abilities to provide innovative solutions to increasingly challenging design problems is a priority in the United States (ABET, 2017; US Department of Commerce, 2012). Though previous studies (Atman, Chimka, Bursic & Nachtmann, 1999; Cross, Christiaans & Dorst, 1994) reported increases in students' abilities to innovate after going through their undergraduate studies, recent studies (Lai, Roan, Greenberg & Yang, 2008; Genco, Holta-Otto & Conner Seepersad, 2012) suggested that students' abilities to provide innovative solutions diminish as they advance through the engineering curriculum. For example, in a 1999 study Atman, et al., who measured creativity in terms of quantity of ideas generated, noted that final year students generated a higher quantity of ideas than second year students. Cross, et al. (1994) measured creativity in terms of quality of ideas generated and found senior students generated a higher quality of ideas than freshmen. In recent studies, Lai, et al. (2008) and Genco, et al. (2012) suggested that while both seniors and freshmen produced ideas of similar quality, seniors were less proficient at creating original solutions to ill-defined problems using creative thinking than freshmen. The conflicting claims warrant further consideration of roles of engineering curricula in developing undergraduate students' abilities to provide innovative solutions to challenging design problems.

While multiple aspects of engineering curricula may impact the development of undergraduate students' abilities to innovate, this research focuses on the roles instructor-assigned design tasks play in fostering students' abilities to provide innovative solutions to challenging problems in the workplace. The instructor-assigned design tasks, which are presented typically in text format to students, form the crux of student experience in cornerstone and capstone courses in engineering (personal experience). Researchers have expressed the need to determine design task characteristics that make design tasks suitable for student learning (Jonassen & Hung, 2008); the need remains unaddressed. This research explored this need by examining the relationships between assigned design task characteristics and undergraduate engineering students' abilities to innovate solutions to design tasks after controlling for students' characteristics that have been identified in previous research as significant predictors of their abilities to innovate solutions.

4.1.1. Definitions and measurement

The literature of learning sciences, psychology, organizational change, and engineering design offer many definitions and methods of measurement of task characteristics (Campbell, 1988; Kim & Soergel, 2005), student characteristics (Amabile, 2013; Lee, 2004) and students' abilities to innovate solutions (Sarkar & Chakrabarti, 2011). This research uses the following definitions and methods of measurement.

4.1.1.1. Task characteristics

Task characteristics are defined by difficulty of a task. Task difficulty, which according to Jonassen, et al. (2008) can be viewed as a combination of task structuredness and task complexity and appears to encompass the majority of the features of a task, was chosen to represent the characteristics of a design task. Task difficulty was measured using a 14-item scale that measures students' perceptions of task structuredness and task complexity (see Lee, 2004 or Appendix A).

4.1.1.2. Student characteristics

Domain-relevant skills, creativity-relevant processes, and task motivation impact students' abilities to innovate solutions to design tasks (Amabile, 2013). Domain-relevant skills were estimated from students' Grade Point Average (GPA), university classification, familiarity with assigned design task, and discipline. GPA is defined as the number of grade points earned divided by number of credit hours attempted (Registrar's office, 2014). University classification is defined as the number of attempted credit hours (Student Rule 13, 2014), and discipline is defined as student's major affiliation. Students self-reported their GPA, classification and discipline. Creativity-relevant processes were estimated with cognitive style. Cognitive style, which is defined as individual differences in orientation towards different problem-solving strategies used to solve a task (Martinsen & Kaufmann, 2011), correlates with personality traits and explains the variance in outcomes beyond the variance explained by personality traits (Martinsen & Kaufmann, 2011). Cognitive style was measured using the Assimilator-Explorer (A-E) inventory. See Appendix C. Task motivation was estimated from current achievement motivation, which is defined as achievement on a task as mitigated by task characteristics. This is because Freund, Kuhn and Holling (2011), who examined measurement issues of the task motivation instrument used in this study, argue that interest (an indicator of current achievement motivation) is a significant predictor of creativity. Task motivation was measured using a short Questionnaire of Current Achievement Motivation (QCM). See Appendix B.

4.1.1.3. Abilities to innovate

While several definitions and methods to measure innovative abilities exist in the literature (Cropley, 2011; O'Quin & Besermer, 2011; Sarkar & Chakrabarti, 2011), abilities to innovate are commonly defined in terms of novelty and usefulness of solutions in engineering. Of the two, novelty - defined as something new/original. (Sarkar, et al., 2011) - was chosen to represent students' abilities to provide innovative solutions. This is because recent literature (Lai, et al., 2008 & Genco, et al., 2012) suggested that originality of student-generated solutions diminishes as undergraduate students advance through the engineering curriculum. Novelty was estimated from students' solutions to a design task based on the rarity of solutions found in the sample..

4.2. Literature

Very few studies were found that explored relationships between characteristics of assigned design tasks and undergraduate students' abilities to innovate after controlling for characteristics such as students' domain-relevant skills, creativity-relevant processes and task motivation. Studies that were found (Reiter-Palmon, Illies, Cross, Buboltz & Nimps, 2009; Jo & Lee, 2012; Martinsen & Kaufmann, 2000) suggested that originality of solutions (at least to everyday tasks) is directly proportional to complexity of said tasks. Quality (another measure of creativity) of solutions, however, appears to be inversely proportional to the complexity of tasks. For example, Reiter-Palmon, et al. (2009), who examined creative performance (i.e. ability to innovate) of psychology students in terms of several indexes of creativity (e.g. solution originality and quality) for three everyday tasks, found that the most complex task invoked the lowest involvement and self-efficacy and had the most original solutions. Average quality of solutions was the lowest for the most complex task among three tasks. Moderate complexity of tasks had most involvement and led to mid-level average originality and quality. The least complex tasks invoked mid-level involvement and had participants produce the least original ideas but high-quality ideas. In Reiter-Palmon, et al.'s study, optimum novelty and quality of solutions was achieved when student motivation to solve a problem is at its highest. They also found that their conclusions varied based on indices used to measure creativity.

Jo and Lee (2012) modeled links among task complexity, intrinsic motivation, organizational. trust (independent variables), and creativity of individuals (dependent variable) working in Korean ICT companies and found that both task complexity and motivation had positive influences on creativity. In their study, intrinsic motivation had the most influence of all independent variables on individual creativity. Martinsen and Kaufmann (2000), who studied effects of task motivation and A-E cognitive style on problem-solving performance, found that highly motivated individuals with explorer cognitive styles underperformed individuals of the same motivation but with assimilator cognitive styles when working on tasks of high difficulty (insight problems). This research sought to determine whether similar findings are true of creativity of engineering students engaged in solving difficult design tasks.

No studies were found that examined relationships between characteristics of design tasks and engineering students' abilities to innovate with the control variables such as students' domain-relevant skills, cognitive style and task motivation as defined in this research. Reiter-Palmon, et al. (2009) and Jo, et al. (2012)'s studies were limited to non-engineering design tasks with students and employees outside of the domain of engineering. In addition, the authors' mapping of the characteristics of the task was limited to problem difficulty measured only in terms of task complexity. Understandably, given the purpose of their studies, Reiter-Palmon, et al. (2009) and Jo, et al. (2012)'s did not use a creativity index specific to the domain of engineering; the metrics used to measure creativity can affect conclusions associated with a study. Martinsen and Kaufmann (2000) did not measure the creative performance of individuals in their study. This research differed in four ways. One, it examined the relationships between task difficulty and novelty with a design task. Two, it used a more encompassing definition of design task characteristics – task difficulty as a function of structuredness and complexity – than previously cited research. Three, a creativity measure specific to the domain of engineering (Sarkar and Chakrabarti, 2011) was used to measure novelty. Four, previously unexamined control variables and population were examined in this research.

4.3. Research Purpose and Question

The purpose of this research was to examine the relationships of structuredness and complexity of an engineering design task to novelty of solutions using a sample of engineering students after controlling for five of their characteristics. The purpose of estimating these relationships after controlling for students' characteristics was to advance research that promotes understanding of learning activities and has implications for education practices that foster abilities to innovate in engineering students. The student characteristics considered in this research are GPA, university classification, familiarity with assigned design task, major, current achievement motivation, and cognitive style. Of these characteristics, only GPA, major, and some facets of current achievement motivation and cognitive style were included in present research. The reason for including only a subset of the characteristics was that only these characteristics were found to be significant predictors of novelty in previous research (Rathore, unpublished). Included facets of current achievement motivation were challenge, anxiety, and interest. Only novelty-seeking orientation facet of cognitive style was included as a control. The research question that was investigated in this research is:

> What are the direct effects of structuredness and complexity of an engineering design task on novelty of solutions developed by engineering students after controlling for their GPA, major, perceived task challenge, task-related anxiety, interest in task and novelty-seeking orientation?

Current research has a three-fold contribution to engineering education. One, it provides a preliminary model and empirical evidence to build theories that eventual.ly explain the relationship between problem characteristics and creativity as moderated and/or mediated by student characteristics. Two, it clarifies potential variance in observed novelty of solutions that design education studies can assign to both design problems and student characteristics when comparing advantages and disadvantages of different ideation techniques. Three, it provides findings about conditions (e.g., characteristics of design task, students) which support novelty in students' solutions. Such findings can inform engineering programs and book publishers about strategies to develop students' abilities to innovate solutions to challenging design problems.

4.4. Methods

A structural equation modeling approach was used to estimate the direct effects of perceived design task structuredness and complexity on novelty of solutions with a sample of engineering students from the target population after controlling for students' GPA, major, challenge, anxiety, interest, and novelty-seeking orientation. This approach is appropriate when independent variables in the model are latent constructs (Rosseel, 2012). The eight independent variables in the structural model were structuredness (STR), complexity (COM), GPA, major, challenge (CH), anxiety (AN), interest (IN) and novelty-seeking orientation (Seeker). The dependent variable was novelty of solutions. It was hypothesized that perceived structuredness, complexity, GPA, major, challenge, anxiety, interest and novelty-seeking orientation directly affect the novelty of student generated solutions. A schematic of the structural equation model is presented in Figure 4.1.

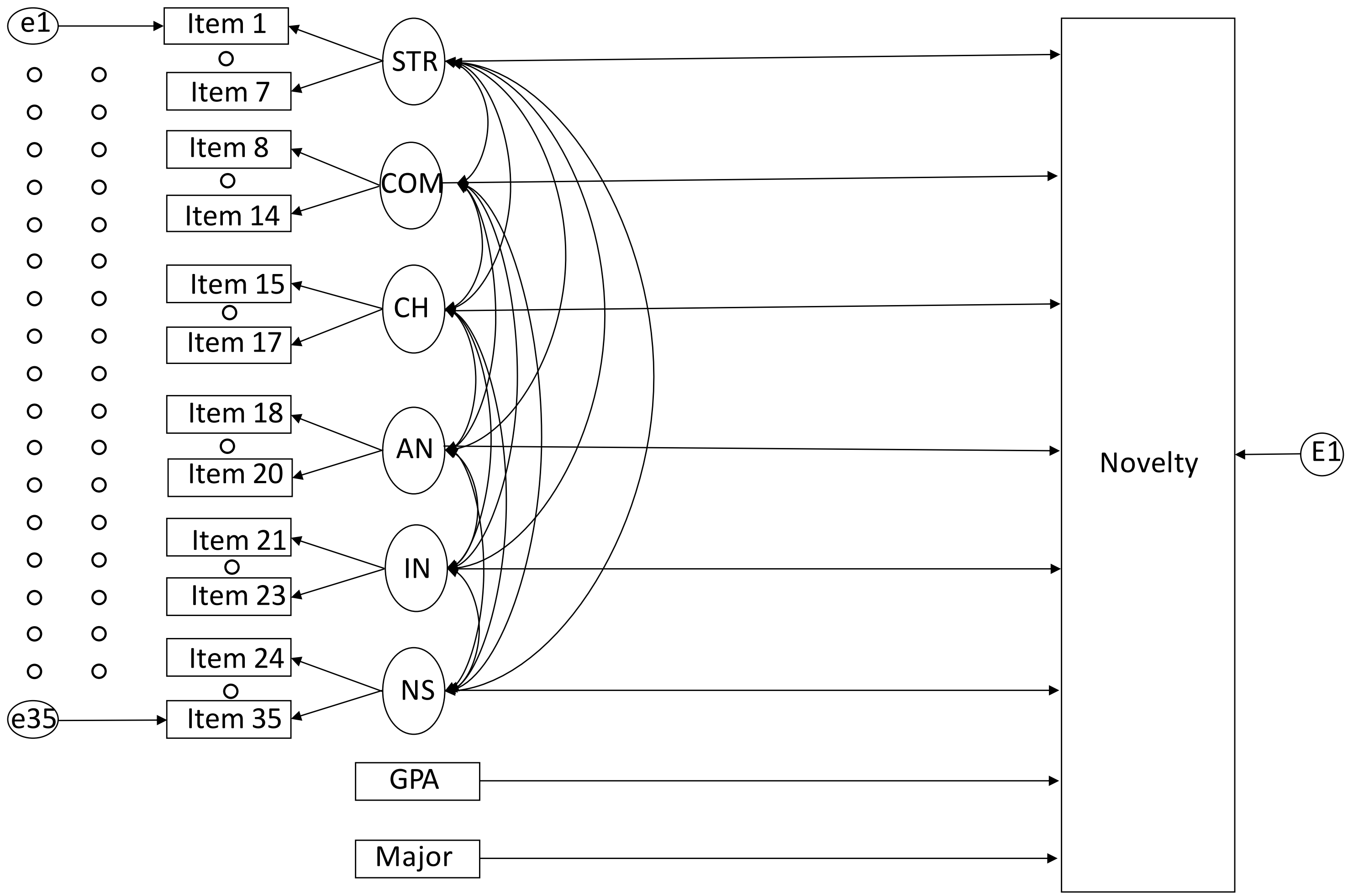

Figure 4.1. Hypothesized casual model to determine the effect of design task structuredness (STR) and complexity (COM) on novelty of solutions with challenge (CH), anxiety (AN), interest (IN), novelty-seeking orientation (NS), Grade Point Average (GPA), and major as covariates. Items measure manifest variables. e or E = measurement error.

4.4.1. Target population

The target population for this research study consisted of all undergraduate engineering students enrolled at a large, research extensive, public university in the southern United States during the 2015-2016 academic year. The average population size was approximately 11263 students. Approximately 21% were females and 78% were males. The population consisted of freshmen (18% - 27%), sophomores (21%), juniors (19% - 22%) and seniors (32% - 38%) over the two semesters. The ranges in classification estimates reflect variability in enrollment over the two academic semesters. The approximate number of students affiliated with each department is presented in Table 4.1. (Texas A&M University – College Station, 2017) The mean Grade Point Average (GPA) of students in the population is not accessible without institutional. permissions and therefore unknown for this research; however, it is presumed to fall between 0.0 and 4.0 because the university computes students' grade point average on a four-point scale.

The target population for this study was selected out of interest from both the US government and industry and researcher's interest and convenience. Both the US government (US Department of Commerce, 2012) and industry have expressed interest in preparing engineering undergraduates with abilities to provide innovative solutions to challenging design problems encountered in the workplaces. Findings derived from research on this population addressed the needs expressed by both the government and industry. Further, present researcher identified needs in the literature to study this population. In addition, the target population was easily accessible via e-mails through the existing network of colleagues, in-person recruitment and experiment visits required of participants.

Table 4.1. Departmental affiliation and approximate percentage of students in the target population during the 2015-2016 academic year

Department affiliation	Students (%)
Aerospace engineering	4
Biological and agricultural engineering	Unknown
Biomedical engineering	2
Chemical engineering	5
Civil engineering	6
College of engineering	28 - 31
Computer science and engineering	8
Electrical and computer engineering	7
Engineering technology and industrial distribution	12 - 13
Industrial and systems engineering	7
Mechanical engineering	9
Nuclear engineering	2
Ocean engineering	1
Petroleum engineering	5

4.4.2. Recruitment and selection

Multiple tactics were used to recruit participants for this research study. First, engineering students with freshmen, sophomore, junior or senior classification were invited to participate in the study via the university bulk-e-mail system. Second, the research study was advertised to students via e-mails through their professors and presentation during class. Third, the researcher made visits to engineering classrooms, primarily capstone design in mechanical engineering, to recruit participants for the research study. The capstone design classrooms were chosen strategical.ly for their high enrollment of students with senior classification.

Students self-selected to participate in the research study using an online study invite form. Use of different recruitment tactics resulted in a participation interest rate of approximately 5 % (~ 600 students). Of the 5% who expressed interest in participating in this research, approximately 60 % visited the research site to participate in the study. Students who consented to participate at the research site constituted the study sample.

4.4.3. Participants

The study sample consisted of 361 undergraduate engineering students. Characteristics of the sample are presented in Table 4.2. As seen from Table 4.2, the sample consists of more mal.es than femal.es. This trend is consistent with the trend about gender observed in the target population. Freshmen and sophomores comprise the majority of participants in the sample. Notably, the two lower-level university classification groups were more amenable to participation in research than juniors and seniors in the population. The majority of participants in the sample are al.so affiliated with either the college of engineering or mechanical engineering. Those who were affiliated with the college of engineering are freshmen who had not yet chosen a major. A high number of mechanical engineering participants resulted from the focused recruitment. A mean GPA of 3.2 is reported for the sample. A mode GPA of 4.0 in the sample suggests that most students who participated in this research are high-achieving students.

Table 4.2. Sample characteristics. Total number of participants is 361.

	N = 361	
Category	n	%
Gender		
Female	143	39.6
Male	217	60.1
Unknown	1	0.3
Classification		
Freshman	114	31.6
Sophomore	104	28.8
Junior	45	12.5
Senior	98	27.1
Department		
Aerospace engineering	15	4.2
Biological and agricultural engineering	1	0.3
Biomedical engineering	-	-
Chemical engineering	18	5.0
Civil engineering	11	3.0
College of engineering	73	20.2
Computer science and engineering	28	7.8
Electrical and computer engineering	29	8.0
Engineering technology and industrial. distribution	15	4.2
Industrial and systems engineering	10	2.8
Mechanical engineering	143	39.6
Nuclear engineering	11	3.0
Ocean engineering	-	-
Petroleum engineering	7	1.9
Familiarity with design task		
Not at all	197	54.6
Very little	131	36.3
Fairly well	21	5.8
Quite well	6	1.7
Perfectly	2	0.6
Not reported	4	1.1

Table 4.2. Continued

	N = 361	
Category	n	%
Grade Point Average (GPA)		
Reported (on 4.0 scale)	303	83.9
Not reported	58	16.1
Mean (standard deviation)	3.2 (0.5)	
Median	3.3	
Mode	4.0	
Range	0.8 – 4.0	

4.4.4. Data collection

Data was collected from participants using a prospective, survey research design approach after obtaining permissions from the university's Institutional. Review Board. Participants completed an online survey after consenting to participate in this research. The survey consisted of three forced-choice categorical items, one forced-choice open-ended item, three forced-choice Likert-scales and one forced-choice brainstorming essay item. Categorical and open-ended items captured demographics variables such as a student's gender (categorical), university classification (categorical), department affiliation (categorical), and GPA (open-ended). The three Likert-scales were measures of task difficulty, QCM, and A-E inventory, respectively. Participants rated their perceptions of task difficulty, motivation to engage with, and general approach to problem-solving in engineering for the assigned design task on the three Likert-scales. In this research, a "mixed wasted [sic] collection" design task was assigned to students. This task required students to develop ideas for separating paper and plastic from a mixed waste collection. The design task was presented to students as follows:

> One of the different systems used for curbside recycling is “mixed wasted collection,” in which all recyclates are collected mixed and the desired material. is then sorted out at a sorting facility. One difficult sorting task is separating paper and plastic, which is usually done by hand. Develop concepts that will enable removing paper or plastic from the mixed collection. (Cheong, Chiu, & Shu, 2010)

The researcher chose to use the mixed waste collection task in this study because of its successful use in idea generation research. In addition, this task was expected to invoke large amounts of variations in students’ responses to perceptions of task difficulty, current achievement motivation and cognitive style. The large amounts of variations are important for establishing group differences, if any, in students’ perceptions of task difficulty and novelty of solutions based on controlled students’ characteristics. Given the task characteristics, the design task is used to examine the direct effects of perceived task difficulty on novelty of solutions after controlling for students’ characteristics. The brainstorming essay item instructed participants to generate as many solutions to the design task as possible in 10-minutes. Participants sketched their ideas on paper and provided textual descriptions of their ideas in the essay item. Participants received monetary compensation for completing the online survey

4.4.5. Data analysis

A two-step structural equation modeling strategy was used to assess the direct effects of design task structuredness and complexity on novelty; challenge, anxiety, interest, novelty-seeking orientation, GPA and major were included as covariates in the model. Measurement models of design task structuredness, design task complexity and manifest covariates were estimated and evaluated "prior to simultaneous estimation of measurement and structural submodels" (Meyers, Gamst, & Guarino, 2012, p. 998) presented in the hypothesized structural equation model (see Figure 4.1). Data were analyzed in R (R Core Team, 2017).

4.4.5.1. Measurement models

Measurement models of structuredness, complexity and manifest covariates were estimated from measures of task difficulty, current achievement motivation, and cognitive style, respectively, using exploratory factor analysis and confirmatory factor with a sample of 361 students. Previous research suggests structuredness and complexity are underlying factors for measures of task difficulty (Jonassen et al., 2008). Challenge, anxiety, interest and probability of success are underlying factors for measures of current achievement motivation (Fruend, et al., 2011). Rules orientation, planning and novelty orientation are underlying factors of measures of cognitive style (Martinsen et al., 2011).

Prior to running an exploratory factor analysis, data on measures of task difficulty, current achievement and cognitive style was scanned for missing values and multivariate outliers. No missing values were identified using a frequency analysis. Multivariate outliers were identified using Mahlabonis distance ($p < 0.001$); however, none were deleted because the researcher had no practical reason for eliminating outliers from the data. Item statistics, included item mean, standard deviation, median, range, skew, kurtosis, and standard errors of skew and kurtosis, were computed. Inter-item polychoric correlation matrices (Fox, 2016), item-total correlation coefficients, standardized ordinal alpha values of scales, and ordinal alpha-if-item-deleted values (Gadermann, Guhn, & Zumbo, 2012) were also estimated to determine item quality. Mardia's Test for multivariate normality (Korkmaz, Goksuluk, & Zararsiz, 2014) was performed for each measure to determine the preferred method of factor extraction.

An exploratory factor analysis was run after item analysis using the psych (Revelle, 2016) package in R to determine measurement models of structuredness, complexity and manifest covariates. Factor solutions were extracted from observed measures using the principal axis factoring method. A promax rotation using the gpaRotation package (Bernaards & Jennrich, 2005) was applied to improve solution interpretability. Decisions about retaining the number of factors for a solution were based on convergence of estimates from four procedures and resulting model plausibility and parsimony. The four procedures that were run to determine the retention of factors were (Matsunaga, 2010; Zygmont & Smith, 2014):

a. *Kaiser's Eigenvalue Criteria*. Factors were retained if eigenvalues resulting from the principal. axis factoring technique and a promax rotation were greater than 1
b. *Cattell's Scree Plot*. Factors were retained if they were within the "sharp bend" on the Scree plot and the communalities were greater than 0.30
c. *Parallel Analysis*. Factors were retained if eigenvalues resulting from the observed correlations matrix were greater than the eigenvalues resulting from a randomly generated correlation matrix of the same size
d. *Velicer's Minimum Average Partial. (MAP) Test*. Factors were retained based on the step that resulted in lowest average squared partial. correlations

Eigenvalue tables and scree plots were generated. Pattern matrices, including factor loadings, communalities, and uniqueness, were computed. Factor correlations and explained variances were estimated using the psych and polychor packages (Fox, 2016). Ordinal alpha values and ordinal alpha-if-item-deleted values (Gadermann, et al., 2012) were also computed to determine if any of the sub-scales could be refined. Factors were labeled based on literature and the type of items that loaded on each factor.

A confirmatory factor analysis (CFA) was conducted next using the lavaan package (Rosseel, 2012) to verify the factor structures found from the EFA. Four fit indices were used to evaluate model fit to actual data. The fit indices are: Chi-Square test of fit and p-value, comparative fit index (CFI), Root Mean Squarer Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). A model was considered acceptable under the following conditions (Awang, 2012):

a. Chi-Square divided by degree of freedom (df) was lower than 3 and P-value was different from zero (greater than 0.05)
b. Comparative Fit Index (CFI) values were above 0.95 (ideal.) or 0.90 (traditional.) or 0.80 (sometimes permissible)
c. Root Mean Square Error of Approximation (RMSEA) values were less than 0.05 (good) or 0.05 – 0.10 (moderate)
d. Standardized Root Mean Square Residual. (SRMR) values were less than 0.09

If the model was found acceptable, convergent and discriminant validity and reliability of factors were computed to further establish the validity and reliability of measures of task difficulty, task motivation and cognitive style. Convergent validity was established if values for the Average Variance Extracted (AVE) were greater than 0.5 and composite reliability (CR) values were found to be greater than 0.7. Divergent validity was established if the following conditions were met:

a. Maximum Shared Variance (MSV) was less than Average Variance Extracted (AVE)
b. Average Shared Variance (ASV) was less than AVE
c. Square root of AVE was greater than inter-construct correlations

In cases (e.g., task difficulty) where models obtained from the EFA were not supported by the CFA, a CFA was run in EFA mode to obtain an acceptable model. Item analyses were run to support decisions regarding item removals. Once acceptable fits were achieved, items that described structuredness, complexity and manifest covariates were extracted from the measures of task difficulty, current achievement motivation and cognitive style for use in the structural equation model.

4.4.5.2. Observed measures

Observed measures of GPA, major and novelty in the structural equation model were screened for missing data. Null GPA values were replaced with the median GPA. While none of the major values were missing, participants who may have similar disciplinary knowledge were re-assigned to the same major category. Majors were re-coded by collapsing categories to achieve an adequate sample size (by decreasing number of predictors) and a non-zero and near thirty cell frequency count to run the structural equation model. The coding sheet for reclassifying majors is presented in Table 4.3. Cases with missing novelty values were removed from further analysis,

Table 4.3. Coding key used to re-classify participants' majors

New Code Description	**Old Code Description**
Classification	
Lower division	Freshman
	Sophomore
Upper division	Junior
	Senior
Department	
Major 1	Aerospace engineering (AERO)
	Civil engineering (CVEN)
	Mechanical engineering (MEEN)
Major 2	Biological and agricultural engineering (BAEN)
	Biomedical engineering (BMEN)
	Chemical engineering (CHEN)
	Nuclear engineering (NUEN)
	Ocean engineering (OCEN)
	Petroleum engineering (PETE)
Major 3	Computer science and engineering (CSEN)
	Electrical and computer engineering (ECEN)
Major 4	Engineering technology and industrial distribution (ETID)
	Industrial and systems engineering (ISEN)
Major 5 (Undeclared)	College of engineering (CLEN)
Familiarity with design task	
Not familiar	Not at all
Familiar	Very little
	Fairly well
	Quite well
	Perfectly

resulting in sample size of 217 participants for the structural equation modeling.

Novelty level of participants' solutions to the design task was assigned based on an analysis of qualitative responses to the brainstorming essay item on the survey. Qualitative responses were first coded into bins with similar ideas. For example, an idea that hinged on separating paper and plastic via optical detection of material properties was put in one bin. An idea that suggested separating paper and plastic using the buoyancy principle was put in another bin. Once all (516) ideas were coded into their respective bins (total. bins: 107), the number of ideas per bin was computed for each bin. The bins were then assigned a "novelty" grade (1-20) based on the number of ideas in the bin. The bin with the highest number of ideas (e.g., 44 ideas) was assigned the lowest grade (e.g., grade = 1). Higher the number of ideas, lower the grade assigned. All bins with the same number of ideas and all ideas inside the same bin were assigned the same grade. After assignment of grades to bins/ideas, an average novelty score of ideas was computed for each participant.

4.4.5.3. Structural equation model

The hypothesized model (Figure 4.1) was analyzed in R using the lavaan package (Rosseel, 2012); the robust full maximum likelihood procedure was used to estimate the model parameters because of violations of normality of distributions. The measurement model was evaluated against fit indices used to evaluate CFA models. Correlations among factors were also analyzed to determine sufficient discriminant and convergent validity among factors. Once an acceptable fit was obtained, all coefficients were evaluated for statistical ($p < 0.05$) and practical (values > 0.30) significance. Findings are presented in the results section.

4.5. Results

The results section describes findings from the measurement model analysis and the structural equation model analysis.

4.5.1. Measurement models: structuredness and complexity

Item, EFA and CFA analyses of 14 observed measures of task difficulty resulted in extraction of 4 observed measures of structuredness and 6 observed measures of complexity. The item analysis, which consisted of frequency analysis, multivariate outlier analysis, and descriptive analysis of measures of task difficulty, found no missing data and several outliers. A complete data set was a result of the forced-choice online survey. Item means, standard deviations, medians, ranges, skew and kurtosis, standard errors of skew and kurtosis, ordinal alpha-if-item deleted, item-total correlations, and inter-item polychoric correlations obtained from the descriptive analysis are presented in Table 4.4 and Table 4.5, respectively. A low overall standardized ordinal alpha value of 0.63 was recorded.

Descriptive analysis results suggested removal of items TD1, TD2, TD6, TD7, TD8, and TD9 from further analysis as their presence may become problematic during factor and reliability analyses. However, removal of these items was problematic. As seen from the corrected item-total correlation values in Table 4, items TD1, TD2, and TD6-TD9 correlate poorly with the rest of items on the scale. Poorly correlated items may not load strongly on extracted factors. In addition, standardized ordinal alpha-if-item-deleted values for items TD1 and TD6-TD8 see an increase if any one of the items is removed from the scale. Therefore, reliability of participants' responses can be improved if problematic items are removed from the scale. Premature deletion of items, however, may result in elimination of facets/factors of task difficulty deemed important in the literature. Therefore, no items were removed prior to the EFA.

Table 4.4. Item statistics (mean, standard deviation (SD), median, range, skew, kurtosis, standard error (SE), ordinal. alpha-if-item deleted, and corrected item-total correlations) for the task difficulty scale. Overall ordinal alpha: 0.63.

	Mean	SD	Median	Range	Skew	Kurtosis	SE	Ordinal Alpha, Item Deleted	Item-Total Correlation
TD1	4.21	0.73	4.00	4.00	-1.29	3.16	0.04	0.67	-0.09
TD2	3.40	1.07	4.00	4.00	-0.43	-0.81	0.06	0.63	0.23
TD3	2.42	1.07	2.00	4.00	0.79	-0.20	0.06	0.59	0.48
TD4	1.53	0.89	1.00	4.00	2.04	4.18	0.05	0.57	0.63
TD5	2.21	1.08	2.00	4.00	0.72	-0.34	0.06	0.57	0.62
TD6	3.76	0.90	4.00	4.00	-0.77	0.27	0.05	0.66	-0.04
TD7	3.49	0.85	4.00	4.00	-0.55	-0.14	0.04	0.64	0.12
TD8	3.31	0.81	3.00	4.00	-0.25	-0.41	0.04	0.64	0.07
TD9	3.14	0.93	3.00	4.00	0.02	-0.53	0.05	0.63	0.21
TD10	2.06	0.85	2.00	4.00	1.08	1.49	0.04	0.56	0.70
TD11	2.13	0.85	2.00	4.00	0.96	0.89	0.04	0.55	0.75
TD12	2.89	1.03	3.00	4.00	0.00	-0.94	0.05	0.59	0.41
TD13	2.05	0.86	2.00	4.00	0.85	0.72	0.05	0.60	0.45
TD14	2.59	0.95	2.00	4.00	0.42	-0.55	0.05	0.59	0.47

Table 4.5. Polychoric correlations for items on a scale of task difficulty

	TD1	TD2	TD3	TD4	TD5	TD6	TD7	TD8	TD9	TD10	TD11	TD12	TD13	TD14
TD1	1													
TD2	0.41	1												
TD3	0.10	0.37	1											
TD4	-0.28	0.23	0.46	1										
TD5	-0.08	0.18	0.37	0.63	1									
TD6	-0.03	-0.23	-0.08	-0.34	-0.08	1								
TD7	0.21	0.22	0.04	0.14	0.20	0.04	1							
TD8	0.00	-0.09	-0.08	-0.12	-0.06	0.12	0.05	1						
TD9	-0.07	0.04	0.00	0.06	0.06	0.07	-0.02	0.10	1					
TD10	-0.27	-0.06	0.19	0.53	0.37	-0.15	-0.10	0.06	0.25	1				
TD11	-0.32	-0.09	0.27	0.49	0.38	-0.02	-0.11	0.04	0.13	0.80	1			
TD12	0.03	0.09	0.16	0.10	0.11	0.10	0.00	0.06	0.20	0.31	0.34	1		
TD13	-0.30	-0.10	0.17	0.39	0.30	-0.09	-0.23	0.04	-0.04	0.47	0.58	0.18	1	
TD14	-0.27	-0.20	0.08	0.18	0.28	0.21	-0.06	0.15	0.11	0.40	0.50	0.19	0.41	1

An observation of the inter-item polychoric correlation matrix (see Table 4.5) suggested use of EFA is appropriate to determine the factor structure of task difficulty.

Modest to moderate correlations between items indicated the presence of an underlying factor structure. For example, items TD3-TD5 modestly correlated with each other. Items TD10, TD11, TD13, and TD14 were also correlated moderately with each other. Further, item analysis indicated use of principal axis factoring with weighted least squares estimation as the extraction method for the EFA. Non-zero skew and kurtosis values, especial.ly for items TD1, TD2, TD4, TD5, TD10, TD11, and TD13, suggested violation of normality. Mardia's test confirmed the violation of multivariate normality, informing the use of principal axis factoring with weighted least squares estimation as method of factor extraction during the EFA.

Procedures for estimating the number of factors indicated extraction of multiple competing solutions (see Table 4.6). While the parallel analysis suggested retention of five factors during the EFA, the eigenvalue greater than one criteria specified extraction of three factors. Both the scree plot (Figure 4.2) and Velicer's MAP analyses suggested extraction of two factors during EFA analysis. Pattern matrices resulting from the extraction of five, three and two factors during EFA are presented in Table 4.7.

Table 4.6. (Eigenvalues from) Parallel analysis, Velicer's minimum average partial. (MAP) correlations, and Eigenvalues (extracted using Principal Axis factoring) for the task difficulty scale

	Parallel Analysis		Velicer MAP	Eigenvalues
	Original Data	Simulated Data		
1	3.20	0.45	0.04	3.27
2	1.29	0.28	0.03	1.24
3	0.53	0.22	0.04	1.14
4	0.28	0.16	0.05	0.95
5	0.17	0.12	0.06	0.81

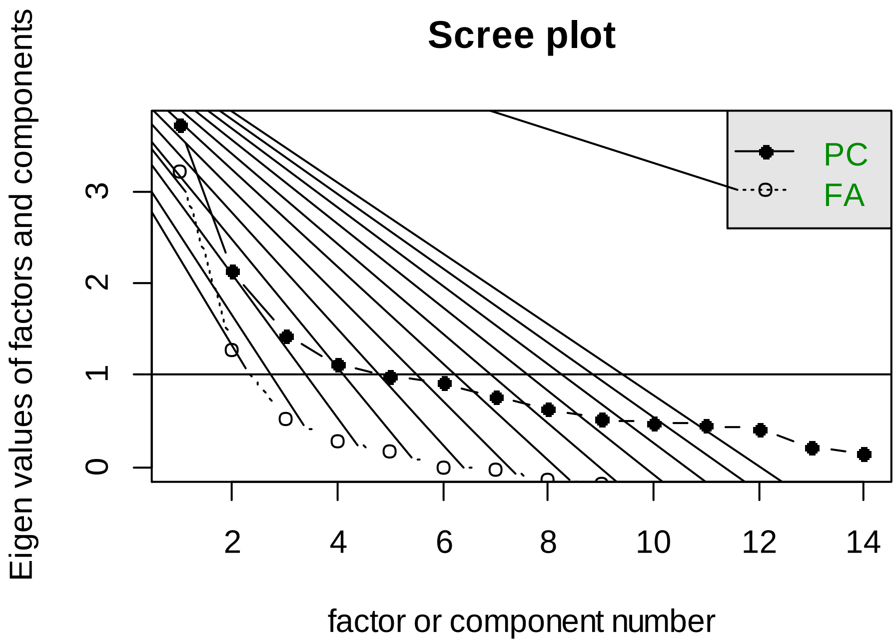

Figure 4.2.Scree plot suggesting extraction of 2 factors of task difficulty

Table 4.7. Pattern matrices resulting from extraction of five, three and two-factor models from 14 observed measures of task difficulty using principal axis factoring and promax rotation. Blanks represent loadings below 0.4. (-) = items removed.

	Five Factor Model							Three Factor Model					Two Factor Model			
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	h2	u2	Factor 1	Factor 2	Factor 3	h2	u2	Factor 1	Factor 2	h2	u2
TD1	-0.40	0.51				0.40	0.60			0.68	0.56	0.44		0.48	0.40	0.60
TD2		0.75				0.61	0.39		0.40	0.78	0.68	0.32		0.80	0.65	0.35
TD3		0.55				0.39	0.61	-	-	-	-	-		0.62	0.46	0.54
TD4	-	-	-	-	-	-	-	0.42	0.71		0.77	0.23	-	-	-	-
TD5	0.53					0.46	0.54		0.45		0.40	0.60	-	-	-	-
TD6			0.86			0.76	0.24		-0.57		0.32	0.68	-	-	-	-
TD7					0.80	0.66	0.34	-	-	-	-	-	-	-	-	-
TD8	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
TD9				0.83		0.70	0.30	-	-	-	-	-	-	-	-	-
TD10	0.80					0.69	0.31	0.76			0.68	0.32	0.81		0.63	0.37
TD11	0.88					0.78	0.22	0.84			0.78	0.22	0.92		0.83	0.17
TD12						0.29	0.71	0.66			0.59	0.41	-	-	-	-
TD13	0.69					0.52	0.48	0.55			0.42	0.58	0.67		0.46	0.54
TD14	0.57					0.44	0.56	-	-	-	-	-	0.56		0.36	0.64

An observation of the pattern matrices of a five-, three- and two-factor solution suggests that a two-factor solution of task difficulty is more plausible compared to a five- or a three-factor solution based on both theory and statistics. The five-factor and three-factor solutions were not supported by theory (Jonassen, et al., 2008) or statistics. The initial pattern matrix for the five-factor solution showed that item TD8 does not load strongly and item TD4 cross-loads with another factor. When items TD8 and TD4 were removed from analysis to obtain a simple structure, item TD12 did not load strongly on any of the five factors. Removal of items "made" the items load on different factors. In addition, only one item loaded strongly on the third, fourth and fifth factor. These features of the five-factor solution made the final solution with an explained variance of 57% statistically unstable and uninterpretable.

Compared to the five-factor solution, the initial three-factor solution was somewhat plausible; however, the pattern matrix showed that items TD7, TD8, TD9 and TD14 did not load strongly on any of the factors. In addition, item TD3 cross-loaded on two factors. Removal of non-loading and cross-loading items resulted in the shown pattern matrix. While a similar amount of variance (58%) was explained by the three-factor solution, a simple structure could not be obtained without making the three-factor solution uninterpretable.

A two-factor model of task difficulty was theoretically and statistically the most plausible model generated during the EFA analysis. The two-factor model loaded items as expected in theory that purports structuredness (Factor 2) and complexity (Factor 1) as two facets of task difficulty. This two factor model is al.so supported by convergence of analysis from the Velicer's MAP and scree plot and presence of a simple structure after removal of non-loading (TD6-TD9, TD12) and cross-loading (TD4, TD5) items. Therefore, a two-factor model was considered for further analysis.

Further analysis, however, put the plausibility of the two-factor model into question. The two-factor model explained only 54% of the variability in responses. A low observed correlation (see Table 4.8) between the two factors made presence of a higher order factor (of task difficulty) debatable. In addition, computed values of standardized ordinal alpha-if-item deleted indicated that reliability of responses to items which load on Factor 2 is low (see Table 4.9). The modest explained variance and the low reliability of responses to items suggested that the two-factor model generated via the EFA analysis might not hold during confirmatory factor analysis.

Table 4.8. Factor correlation matrix for a two factor model of task difficulty

	Factor 1	Factor 2
Factor 1	1	-0.18
Factor 2	-0.18	1

Table 4.9. Standardized ordinal. alpha-if-item deleted and item-to-total. scale correlations for a two factor model representative of task difficulty

	Ordinal Alpha	Item-Total Correlations
Factor 1	0.55	
TD1	0.54	0.45
TD2	0.18	0.69
TD3	0.58	0.4
Factor 2	0.82	
TD10	0.75	0.8
TD11	0.69	0.9
TD13	0.8	0.63
TD14	0.83	0.55

Fit indices obtained from the CFA for the two-factor model of task difficulty confirmed that the model obtained from the EFA analysis required revisions. For example, the Chi-Square fit index of 12.30 (df = 13, p = 0) was above the acceptable threshold of 3 for the EFA model. While a CFI value of 0.95 was acceptable, the RMSEA and SRMR values of 0.18 and 0.11 respectively were outside the acceptable range for a well-fitting model, suggesting model revisions.

A well-fitting model of task difficulty was obtained when the CFA analysis was run in exploratory mode. This model consisted of two factors – structuredness and complexity – with a factor correlation of 0.59. The model resulted from deletion of items (TD1, TD2, TD6 and TD8) with poor to no item-to-total scale correlations and ordinal alpha values higher than the overall standardized ordinal alpha value. The Chi-Square fit index of 2.85 (df = 34) was below the suggested threshold of 3. The CFI, RMSEA and SRMR values of 0.98, 0.07, and 0.07, respectively, were within the acceptable ranges for a well-fitting model. While the model did not meet criteria for convergent validity completely, divergent validity was established for this model (See Table 4.10). The lack of convergent validity is attributable to the low reliability of responses to items that load on Factor 1. Nevertheless, the two-factor model was considered plausible with strong basis in theory and statistical support.

Table 4.10. Values of AVE, MSV, ASV and CR and covariance between factors of a two factor model of task difficulty

Factor	Measures				Standardized Covariance	
	AVE	MSV	ASV	CR	Factor 1	Factor 2
Factor 1	0.40	0.35	0.35	0.65	1	
Factor 2	0.40	0.35	0.35	0.77	0.59	1

4.5.2. Measurement models: challenge, anxiety and interest

An item, EFA, and CFA analysis of 12 observed measures of current achievement motivation resulted in extraction of 2 observed measures of challenge, 3 observed measures of anxiety, and 3 observed measures of interest. The item analysis, which consisted of frequency analysis, multivariate outlier analysis, and descriptive analysis of measures of task motivation, found no missing data and several outliers. A complete data set was a result of the forced-choice online survey. Item means, standard deviations, medians, ranges, skew and kurtosis, standard errors of skew and kurtosis, ordinal alpha-if-item deleted, item-total correlations, and inter-item polychoric correlations obtained from the descriptive analysis are presented in Table 4.11 and Table 4.12, respectively. A modest overall standardized ordinal. alpha value of 0.72 was recorded.

Table 4.11. Item statistics (mean, standard deviation (SD), median, range, skew, kurtosis, standard error (SE), ordinal alpha-if-item deleted, and corrected item-total correlations) for the scale of current achievement motivation. Overall ordinal alpha: 0.72.

	Mean	SD	Median	Range	Skew	Kurtosis	SE	Ordinal Alpha, Item Deleted	Item-Total Correlation
TM1	5.65	0.96	6.00	5.00	-0.94	1.44	0.05	0.71	0.37
TM2	5.14	1.27	5.00	6.00	-0.57	-0.27	0.07	0.73	0.27
TM3	3.86	1.75	4.00	6.00	-0.09	-1.24	0.09	0.72	0.25
TM4	4.93	1.46	5.00	6.00	-0.83	0.07	0.08	0.67	0.71
TM5	5.30	1.32	5.00	6.00	-0.88	0.68	0.07	0.67	0.67
TM6	3.10	1.76	3.00	6.00	0.53	-0.84	0.09	0.73	0.29
TM7	5.51	1.25	6.00	6.00	-0.97	0.76	0.07	0.68	0.59
TM8	4.37	1.52	4.00	6.00	-0.29	-0.60	0.08	0.69	0.53
TM9	3.40	1.84	3.00	6.00	0.32	-1.14	0.10	0.74	0.19
TM10	3.73	1.65	4.00	6.00	0.08	-0.95	0.09	0.73	0.18
TM11	5.39	1.24	6.00	6.00	-0.81	0.63	0.07	0.68	0.59
TM12	3.83	1.67	4.00	6.00	-0.03	-0.97	0.09	0.66	0.72

Descriptive analysis results suggested running an EFA with principal axis factoring with weighted least square as method of estimation on all 12 measures of task motivation. As seen from Table 4.12, multiple items on the task motivation scale share a modest to moderate inter-item polychoric correlations with each other. For example, items TM1, TM2, TM4 and TM5 are modestly correlated with each other. Items TM5, TM7, TM8, TM11, and TM12 are al.so correlated with each other. Presence of modest inter-item correlations indicates presence of an underlying structure that could be determined through an EFA. Skew and kurtosis values observed from Table 4.11 indicated that normality may be violated. Mardia's Test of multivariate normality confirmed violation of normality and use of principal axis factoring as the method of factor extraction. Ordinal alpha values and item-to-total correlations indicated that reliability of responses to measures of task motivation may be improved if items TM2, TM6, TM9 and TM10 are removed from the task motivation scale. However, none of these items were removed prior to the EFA to eliminate premature deletion of facets identified as important in the literature on task motivation.

Table 4.12. Polychoric correlations for items on the current achievement motivation scale

	TM1	TM2	TM3	TM4	TM5	TM6	TM7	TM8	TM9	TM10	TM11	TM12
TM1	1											
TM2	0.61	1										
TM3	-0.20	-0.19	1									
TM4	0.35	0.19	0.07	1								
TM5	0.42	0.25	0.04	0.70	1							
TM6	-0.37	-0.33	0.50	0.03	-0.07	1						
TM7	0.24	0.23	0.12	0.44	0.54	0.06	1					
TM8	0.15	0.06	0.06	0.48	0.42	0.01	0.33	1				
TM9	-0.16	-0.09	0.37	-0.11	-0.21	0.65	-0.11	-0.15	1			
TM10	0.10	0.07	-0.01	0.10	-0.03	0.14	0.01	0.20	0.14	1		
TM11	0.12	0.10	0.21	0.41	0.40	0.21	0.50	0.26	0.09	0.01	1	
TM12	0.24	0.12	0.13	0.58	0.51	0.13	0.38	0.59	0.05	0.12	0.49	1

Procedures for estimating the number of factors (Table 4.13) led to extraction of three competing solutions that were contrary to the four-factor theoretical solution. The Parallel Analysis suggested extraction of a five-factor solution. The eigenvalues greater than or equal to one criteria indicated extraction of a three-factor solution. Both the Velicer’s MAP and the scree plot (Figure 4.3) converged at a two-factor solution.

Table 4.13. (Eigenvalues from) Parallel analysis, Velicer's minimum average partial (MAP) correlations, and Eigenvalues (extracted using Principal Axis factoring) for the current achievement motivation scale

	Parallel Analysis		Velicer MAP	Eigenvalues
	Original Data	Simulated Data		
1	3.14	0.43	0.05	2.74
2	1.52	0.24	0.04	1.55
3	0.35	0.19	0.05	1.20
4	0.33	0.13	0.06	0.53
5	0.10	0.09	0.08	0.33

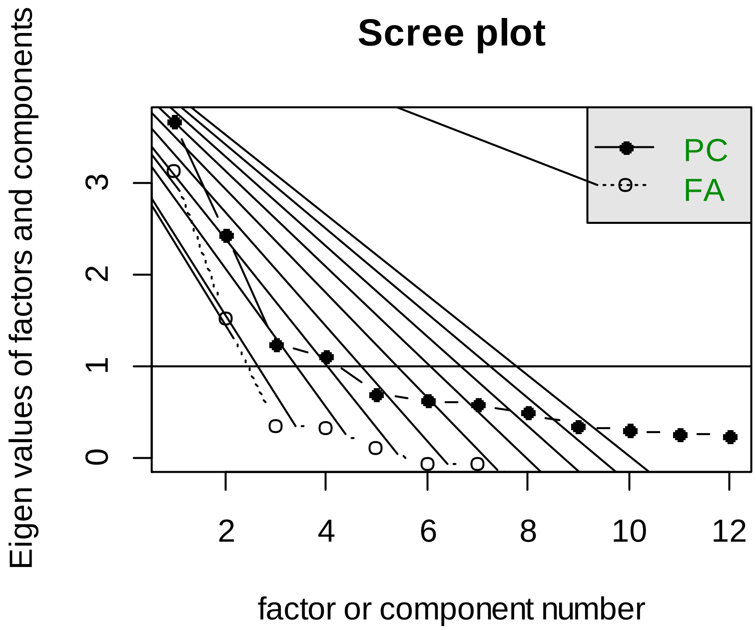

Figure 4.3. Scree plot suggesting extraction of 2 or 3 factors from observed measures of task motivation

Pattern matrices resulting from the extraction of four- (theoretical), three-, and two-factor solutions from the EFA are presented in Table 4.14. An observation of the pattern matrices of a five- (not shown), four-, three- and two-factor solutions of current achievement motivation suggests that priority should be given to a four-factor solution based on theory and statistics. The five-factor solution was not supported by theory. In addition, an analysis of the five factor pattern matrix showed none of the items loaded strongly (> 0.4) on the fifth factor. The four-factor solution was found supported by the current achievement motivation theory (Fruend, et al., 2011) and statistics. The four-factor solution explained most variance (55%) in students' responses after deletion of items TM10 and TD8. The factor correlation matrix for the four-factor solution is presented in Table 4.15. Item reliability analysis indicated fair reliability of all but the fourth factor (See Table 4.16). The three-factor solution was not supported by theory but explained 52% of the explained variance. The two-factor solution was supported by an alternate theory – the approach-avoidance theory of motivation (Elliot & Thrash, 2002) – but explained only 49% of the variance. Since items TM1-TM12 were derived from the current achievement motivation theory and a four-factor solution explains most variance in participants' responses, the four-factor solution was confirmed via confirmatory factor analysis.

Fit indices obtained from the CFA supported the presence of a four-factor model of current achievement motivation generated through the EFA analysis. While the Chi Square index of fit was slightly above the acceptable threshold of 3 (Chi Square = 122, df = 3, p = 0), other fit indices were within the acceptable ranges of model fit. For example, the CFI value was 0.95. The RMSEA and SRMR values were 0.09 and 0.06, respectively. Given at least three indices met criteria for a well-fitting model, the four-factor model was accepted for further analysis.

Table 4.14. Pattern matrices resulting from extraction of four-, three- and two-factor models from 12 observed measures of current achievement motivation using principal axis factoring and promax rotation. Blanks represent loadings below 0.4. (-) = items removed.

	Four Factor Model						Three Factor Model					Two Factor Model			
	Factor 1	Factor 2	Factor 3	Factor 4	h2	u2	Factor 1	Factor 2	Factor 3	h2	u2	Factor 1	Factor 2	h2	u2
TM1			0.68		0.60	0.40			0.68	0.59	0.41	-	-	-	-
TM2			0.75		0.52	0.48			0.72	0.51	0.49	-	-	-	-
TM3		0.44			0.33	0.67		0.49		0.32	0.68		0.55	0.32	0.68
TM4	0.85				0.65	0.35	0.76			0.61	0.39	0.78		0.61	0.39
TM5	0.75				0.67	0.33	0.74			0.64	0.36	0.79		0.62	0.38
TM6		0.73			0.70	0.30		0.74		0.70	0.30		0.79	0.62	0.38
TM7				0.50	0.48	0.52	0.58			0.40	0.60	0.63		0.39	0.61
TM8	-	-	-	-	-	-	0.68			0.42	0.58	0.62		0.38	0.62
TM9		0.87			0.59	0.41		0.81		0.58	0.42		0.74	0.55	0.45
TM10	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
TM11				0.41	0.45	0.55	0.55			0.40	0.60	0.57		0.40	0.60
TM12	0.65				0.48	0.52	0.75			0.57	0.43	0.73		0.56	0.44

Table 4.15. Factor correlation matrix for a four-factor model of current achievement motivation

	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1	1			
Factor 2	0.03	1		
Factor 3	0.35	-0.43	1	
Factor 4	0.59	0.38	0.01	1

Table 4.16. Standardized ordinal alpha-if-item deleted and item-to-total scale correlations for factors representative of a four-factor model of current achievement motivation. (*) = items reversed

	Ordinal Alpha	Item-Total Correlations
Factor 1	0.82	
TM4	0.67	0.82
TM5	0.73	0.77
TM12	0.83	0.64
Factor 2	0.75	
TM3	0.78	0.55
TM6	0.54	0.8
TM9	0.66	0.7
Factor 3	0.76	
TM1	0.61	0.7
TM2*	0.61	0.7
Factor 4	0.66	
TM7	0.5	0.61
TM11	0.5	0.61

Convergent and divergent validity analyses provided mixed evidence for validity of the four-factor model of current achievement motivation. Evidence (see Table 4.17) found from the convergent validity analysis suggested item convergence for all but factor 4. Composite reliability of factor 4 was lower than the acceptable threshold of 0.70. The low convergence for factor four may be due to item quality, few measurement items, or sample size. Divergent analysis suggested factor 1 and factor 4 cannot be distinguished from each other. Possible explanations include poor reliability of responses on factor 4, high inter-construct correlation, and small sample size.

Table 4.17.Values of AVE, MSV, ASV and CR and covariance among factors of a four-factor model of current achievement motivation

Factor	Measures				Standardized Covariance			
	AVE	MSV	ASV	CR	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1	0.56	0.56	0.23	0.79	1			
Factor 2	0.56	0.17	0.07	0.78	0.06	1		
Factor 3	0.64	0.17	0.13	0.77	0.34	-0.41	1	
Factor 4	0.49	0.56	0.22	0.66	0.75	0.20	0.32	1

Nonetheless, acknowledging limited evidence of convergent and divergent validity, measures that represent interest (factor 1), anxiety (factor 2), and challenge (factor 4) were extracted from the questionnaire on current achievement motivation for structural equation model (SEM) analysis. Use of items from both factor 1 and factor 4 in the SEM model was justified (a) based on theory that supports presence of two distinguishable factors, (b) availability of previous evidence (Fruend et al., 2008) that supported presence of two distinguishable factors using a large sample size, and (c) attribution of high inter-construct correlation to presence of a higher-order construct (student engagement) instead of absence of two different constructs.

4.5.3. Measurement model: novelty-seeking orientation

Item analysis, EFA and CFA of 30 observed measures of cognitive style resulted in extraction of 11 observed measures of novelty-seeking orientation. The item analysis, which consisted of frequency analysis, multivariate outlier analysis and descriptive analysis of measures of cognitive style, found no missing data and several outliers. A complete data set was a result of the forced-choice online survey. Item means, standard deviations, medians, ranges, skew and kurtosis, standard errors of skew and kurtosis, ordinal. alpha-if-item deleted, item-total correlations, and inter-item polychoric correlations obtained from the descriptive analysis are presented in Table 4.18 and Table 4.19, respectively. A moderate overall standardized ordinal alpha value of 0.87 was recorded.

Descriptive analysis results suggested running an EFA using principal axis factoring as method of extraction and weighted least squares estimation method on 30 measures of cognitive style. As seen from Table 4.19, multiple items on the cognitive style scale share a modest to moderate inter-item polychoric correlations with each other. For example, items CS2-CS6 and CS8-CS10 are modestly correlated with each other. Items CS18-CS22 are also correlated with each other. Presence of modest inter-item correlations indicates existence of an underlying structure that could be determined through an EFA. Non-zero values of skew and kurtosis observed from Table 4.18 indicated a possible normality violation. Mardia's Test of multivariate normality confirmed violation of normality and suggested use of principal axis factoring as the method of factor extraction. Ordinal alpha values and item-to-total correlations indicated that reliability of responses might improve if items CS1, CS11, CS27 are removed from the cognitive style scale. However, none of these items were removed prior to the EFA to avoid premature deletion of facets identified as important in the cognitive style literature.

Table 4.18. Item statistics (mean, standard deviation (SD), median, range, skew, kurtosis, standard error (SE), ordinal alpha-if-item deleted, and corrected item-total correlations) for the cognitive style scale. Overall ordinal alpha: 0.87

	Mean	SD	Median	Range	Skey	Kurtosis	SE	Ordinal Alpha, Item Deleted	Item-Total Correlation
CS1	2.11	0.81	2.00	4.00	0.54	0.14	0.04	0.88	0.19
CS2	2.70	0.90	3.00	4.00	0.30	-0.51	0.05	0.87	0.52
CS3	2.34	0.89	2.00	4.00	0.49	-0.25	0.05	0.87	0.55
CS4	2.94	0.99	3.00	4.00	-0.03	-0.87	0.05	0.87	0.50
CS5	1.96	0.83	2.00	4.00	0.73	0.27	0.04	0.87	0.54
CS6	2.70	1.05	3.00	4.00	0.27	-0.72	0.06	0.87	0.60
CS7	2.34	0.93	2.00	4.00	0.55	-0.03	0.05	0.87	0.46
CS8	2.58	1.04	2.00	4.00	0.35	-0.65	0.05	0.87	0.61
CS9	2.34	0.94	2.00	4.00	0.71	0.12	0.05	0.87	0.56
CS10	1.92	0.85	2.00	4.00	1.12	1.58	0.04	0.87	0.45
CS11	2.38	0.93	2.00	4.00	0.42	-0.44	0.05	0.88	0.22
CS12	2.77	0.91	3.00	4.00	0.40	-0.41	0.05	0.87	0.45
CS13	2.42	0.90	2.00	4.00	0.68	-0.05	0.05	0.87	0.46
CS14	2.18	0.78	2.00	4.00	0.85	1.01	0.04	0.87	0.46
CS15	3.20	0.98	3.00	4.00	-0.01	-0.80	0.05	0.87	0.48
CS16	3.50	0.96	4.00	4.00	-0.39	-0.56	0.05	0.87	0.58
CS17	3.57	1.05	4.00	4.00	-0.41	-0.67	0.06	0.87	0.38
CS18	3.58	1.01	4.00	4.00	-0.32	-0.70	0.05	0.87	0.51
CS19	3.37	1.04	4.00	4.00	-0.17	-0.91	0.05	0.87	0.60
CS20	4.54	0.97	5.00	5.00	-0.54	-0.05	0.05	0.87	0.40
CS21	2.95	1.03	3.00	4.00	0.15	-0.71	0.05	0.87	0.57
CS22	2.93	1.00	3.00	4.00	0.14	-0.70	0.05	0.87	0.59
CS23	3.87	0.80	4.00	4.00	-0.69	0.44	0.04	0.87	0.42
CS24	3.53	0.87	4.00	4.00	-0.13	-0.57	0.05	0.87	0.44
CS25	3.84	0.86	4.00	4.00	-0.78	0.40	0.05	0.87	0.34
CS26	3.56	0.94	4.00	4.00	-0.30	-0.59	0.05	0.87	0.59
CS27	3.52	0.92	4.00	4.00	-0.45	-0.24	0.05	0.89	-0.49
CS28	3.17	1.08	3.00	4.00	-0.04	-1.02	0.06	0.87	0.45
CS29	2.46	1.01	2.00	4.00	0.54	-0.29	0.05	0.87	0.55
CS30	2.27	0.85	2.00	4.00	0.64	0.15	0.04	0.87	0.31

Table 4.19. Polychoric correlations for items on scale of cognitive style

	CS1	CS2	CS3	CS4	CS5	CS6	CS7	CS8	CS9	CS10	CS11	CS12	CS13	CS14	CS15	CS16	CS17	CS18	CS19	CS20	CS21	CS22	CS23	CS24	CS25	CS26	CS27	CS28	CS29	CS30
CS1	1																													
CS2	0.23	1																												
CS3	0.17	0.43	1																											
CS4	0.06	0.33	0.47	1																										
CS5	0.12	0.39	0.45	0.31	1																									
CS6	0.18	0.48	0.31	0.25	0.45	1																								
CS7	0.25	0.26	0.22	0.16	0.38	0.44	1																							
CS8	0.13	0.36	0.36	0.30	0.30	0.48	0.46	1																						
CS9	0.04	0.32	0.36	0.31	0.37	0.41	0.30	0.45	1																					
CS10	0.05	0.35	0.36	0.17	0.39	0.30	0.35	0.39	0.41	1																				
CS11	0.41	0.13	0.07	0.07	0.12	0.17	0.30	0.25	0.14	0.14	1																			
CS12	0.07	0.36	0.39	0.24	0.31	0.33	0.23	0.27	0.31	0.33	0.06	1																		
CS13	0.24	0.38	0.36	0.26	0.29	0.19	0.36	0.40	0.35	0.32	0.32	0.30	1																	
CS14	0.03	0.27	0.36	0.14	0.36	0.37	0.32	0.35	0.32	0.45	0.21	0.44	0.39	1																
CS15	-0.06	0.09	0.19	0.25	0.16	0.24	0.08	0.15	0.15	0.09	-0.12	0.27	0.05	0.31	1															
CS16	0.00	0.21	0.24	0.29	0.15	0.26	0.10	0.18	0.25	0.13	-0.08	0.30	0.09	0.14	0.49	1														
CS17	-0.05	0.23	0.11	0.15	0.18	0.20	0.03	0.21	0.20	0.21	-0.02	0.15	0.10	0.08	0.21	0.22	1													
CS18	0.05	0.20	0.16	0.24	0.21	0.26	0.23	0.29	0.14	0.07	0.00	0.14	0.16	0.10	0.46	0.40	0.22	1												
CS19	0.07	0.19	0.15	0.35	0.12	0.25	0.17	0.39	0.34	0.18	0.18	0.16	0.21	0.12	0.41	0.47	0.23	0.42	1											
CS20	-0.01	0.14	0.23	0.15	0.16	0.19	0.12	0.16	0.15	0.11	-0.10	0.17	0.01	0.16	0.36	0.38	0.16	0.31	0.28	1										
CS21	0.01	0.17	0.26	0.21	0.21	0.30	0.21	0.21	0.20	0.16	0.05	0.25	0.15	0.23	0.41	0.55	0.17	0.36	0.39	0.34	1									
CS22	-0.04	0.12	0.40	0.31	0.30	0.20	0.14	0.28	0.37	0.18	0.04	0.10	0.09	0.15	0.25	0.38	0.32	0.38	0.35	0.27	0.41	1								
CS23	-0.11	0.10	0.17	0.29	0.10	0.13	0.03	0.19	0.14	-0.01	-0.16	-0.01	-0.03	0.01	0.32	0.36	0.31	0.38	0.24	0.35	0.30	0.59	1							
CS24	-0.06	0.19	0.24	0.26	0.29	0.23	-0.01	0.28	0.31	0.15	-0.11	0.13	0.07	0.06	0.20	0.26	0.36	0.26	0.27	0.25	0.17	0.41	0.38	1						
CS25	-0.05	0.08	0.07	0.22	0.06	0.08	0.01	0.16	0.08	0.01	0.04	0.12	0.14	0.06	0.20	0.29	0.16	0.27	0.28	0.16	0.20	0.26	0.24	0.24	1					
CS26	-0.02	0.24	0.27	0.36	0.16	0.34	0.11	0.29	0.22	0.09	-0.05	0.26	0.10	0.14	0.39	0.49	0.29	0.39	0.43	0.26	0.47	0.46	0.47	0.36	0.34	1				
CS27	-0.19	-0.27	-0.29	-0.17	-0.41	-0.42	-0.32	-0.39	-0.33	-0.30	-0.20	-0.30	-0.39	-0.37	-0.12	-0.10	-0.11	-0.19	-0.16	-0.06	-0.18	-0.23	-0.05	-0.17	-0.05	-0.20	1			
CS28	0.21	0.18	0.08	0.13	0.14	0.21	0.22	0.23	0.16	0.04	0.23	0.02	0.21	0.06	0.20	0.30	0.19	0.19	0.38	0.15	0.31	0.24	0.18	0.22	0.26	0.28	-0.25	1		
CS29	0.15	0.16	0.15	0.13	0.38	0.38	0.20	0.22	0.39	0.27	0.10	0.16	0.29	0.27	0.28	0.32	0.21	0.27	0.38	0.22	0.43	0.35	0.20	0.14	0.17	0.30	-0.32	0.39	1	
CS30	0.29	0.13	0.07	0.06	0.23	0.18	0.24	0.22	0.20	0.17	0.35	0.05	0.29	0.13	-0.03	0.08	0.08	0.04	0.17	-0.01	0.13	0.14	-0.04	0.09	0.14	0.06	-0.51	0.40	0.29	1

Procedures for estimating the number of factors suggested extraction of four competing solutions (see Table 4.20). While the Parallel Analysis indicated extraction of a five-factor model, the eigenvalue greater than one criteria supported extraction of a four-factor model. Velicer's MAP and scree plot (Figure 4.4) suggested extraction of a three-factor model and a two-factor model, respectively. With the exception of the five-factor model, pattern matrices for the competing solutions are presented in Table 4.21.

Table 4.20. (Eigenvalues from) Parallel analysis, Velicer's minimum average partial (MAP) correlations, and Eigenvalues (extracted using Principal Axis factoring) for the cognitive style scale

	Parallel Analysis		Velicer MAP	Eigenvalues
	Original Data	Simulated Data		
1	6.96	0.64	0.02	3.99
2	2.48	0.51	0.01	3.35
3	1.10	0.45	0.01	2.23
4	0.68	0.40	0.01	2.37
5	0.48	0.36	0.01	0.91

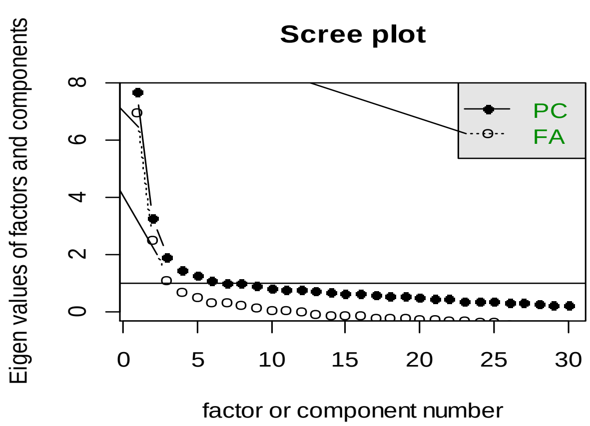

Figure 4.4. Scree plot suggesting extraction of 2 factors from observed measures of cognitive style

Table 4.21.Pattern matrices resulting from extraction of four, three, and two factor models from 30 observed measures of cognitive style using principal axis factoring and promax rotation. Blanks represent loadings below 0.4. (-) = items removed.

	Four Factor Model						Three Factor Model					Two Factor Model			
	Factor 1	Factor 2	Factor 3	Factor 4	h2	u2	Factor 1	Factor 2	Factor 3	h2	u2	Factor 1	Factor 2	h2	u2
CS1			0.56		0.3	0.7			0.53	0.29	0.71	-	-	-	-
CS2		0.55			0.38	0.62		0.56		0.37	0.63		0.58	0.34	0.66
CS3		0.61			0.43	0.57		0.64		0.43	0.57		0.52	0.36	0.64
CS4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
CS5		0.6			0.43	0.57		0.63		0.41	0.59		0.59	0.37	0.63
CS6		0.48			0.39	0.61		0.5		0.39	0.61		0.57	0.41	0.59
CS7	-	-	-	-	-	-	-	-	-	-	-		0.61	0.34	0.66
CS8	-	-	-	-	-	-	-	-	-	-	-		0.6	0.44	0.56
CS9		0.47			0.4	0.6		0.51		0.37	0.63		0.55	0.37	0.63
CS10		0.66			0.38	0.62		0.66		0.37	0.63		0.65	0.38	0.62
CS11			0.67		0.44	0.56			0.67	0.44	0.56		0.42	0.15	0.85
CS12		0.66			0.42	0.58		0.62		0.35	0.65		0.5	0.29	0.71
CS13		0.42			0.39	0.61		0.4		0.39	0.61		0.64	0.35	0.65
CS14		0.72			0.46	0.54		0.69		0.41	0.59		0.64	0.38	0.62
CS15	0.72				0.51	0.49	0.56			0.38	0.62	0.6		0.35	0.65
CS16	0.7				0.54	0.46	0.69			0.49	0.51	0.7		0.49	0.51
CS17				0.4	0.22	0.78	-	-	-	-	-	-	-	-	-
CS18	0.53				0.39	0.61	0.64			0.38	0.62	0.59		0.37	0.63
CS19	0.57				0.45	0.55	0.64			0.44	0.56	0.52		0.35	0.65
CS20	0.4				0.27	0.73	0.45			0.26	0.74	0.5		0.25	0.75
CS21	0.62				0.44	0.56	0.59			0.4	0.6	0.56		0.38	0.62
CS22				0.73	0.6	0.4	0.65			0.46	0.54	0.62		0.43	0.57
CS23				0.65	0.54	0.46	0.7			0.46	0.54	0.73		0.44	0.56
CS24				0.59	0.38	0.62	0.42			0.25	0.75	0.46		0.24	0.76
CS25	-	-	-	-	-	-	0.47			0.19	0.81	0.41		0.16	0.84
CS26	0.48				0.48	0.52	0.7			0.49	0.51	0.7		0.5	0.5
CS27	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
CS28	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
CS29	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
CS30			0.52		0.28	0.72			0.52	0.28	0.72	-	-	-	-

An analysis and observation of the competing solutions supported the use of a two-factor model of cognitive style for further analysis. Of the four solutions, the five-factor model, which explained most variance (43%), was found unstable and uninterpretable due to strong loading of only one item on the fifth factor and strong cross-loading of items on multiple factors. Therefore, the five-factor model was not considered for further analysis. Of the other factor models, the EFA results showed that the four-factor model explained the most and a similar amount of variance (41%) to the five-factor model after deletion of multiple weak loading items (CS4, CS8, CS25, CS27, CS29) and incorrectly loading item (CS28). The three-factor model explained a lower amount (38%) of the variances in participants' responses compared to the four-factor model after deletion of multiple weak loading items (CS4, CS7, CS8, CS17, CS27-CS29). The two-factor model explained the least amount (35%) of variation in responses, had factor correlation of 0.42 (see Table 4.22), and high reliability of responses. Ordinal alpha and item-total correlation values for the two-factor model are presented in Table 4.23. Given the small difference (3% and 6%) in explained common variance between models, the two-factor model was selected for further analysis on basis of theory (Martinsen et al., 2011), plausibility (items belong on respective factors; high reliability) and parsimony (lowest number of factors).

Table 4.22. Correlation matrix for a two factor model of cognitive style

	Factor 1	Factor 2
Factor 1	1	0.42
Factor 2	0.42	1

CFA corroborated selection of a two-factor model of cognitive style. Fit indices for the four-, three- and two-factor models demonstrated similar, well-fitting models. For example, the Chi-Square fit indices for the four-, three- and two-factor model were 2.08, 2.30, and 2.45, respectively. The CFI values were 0.97, 0.96, and 0.96, respectively. The RMSEA values were 0.06, 0.06, and 0.07, respectively. The SRMR values for all three models were 0.07. Since all models were plausible on basis of fit, the two-factor model was selected for further analysis based on theory and parsimony.

Table 4.23. Standardized ordinal alpha-if-item deleted and item-to-total scale correlations for factors representative of cognitive style.

	Ordinal Alpha	Item-Total Correlations
Factor 1	0.85	
CS15	0.84	0.59
CS16	0.83	0.7
CS18	0.84	0.61
CS19	0.84	0.6
CS20	0.85	0.5
CS21	0.84	0.62
CS22	0.84	0.65
CS23	0.84	0.63
CS24	0.85	0.47
CS25	0.85	0.41
CS26	0.83	0.7
Factor 2	0.85	
CS2	0.84	0.6
CS3	0.84	0.58
CS5	0.84	0.61
CS6	0.84	0.64
CS7	0.84	0.58
CS8	0.84	0.65
CS9	0.84	0.59
CS10	0.84	0.6
CS11	0.86	0.3
CS12	0.84	0.53
CS13	0.84	0.59
CS14	0.84	0.62

Convergent and divergent validity analysis further supported the plausibility of a two-factor model, allowing for extraction of a measurement model for representing novelty-seeking orientation. Convergent validity analysis for the two-factor model showed that while the average variance explained by individual was less than 50%, the combined average variance explained was 70%. The composite reliability of responses to items on each factor was greater than 0.80 (see Table 4.24). Criteria for divergent analysis were met, indicating factor 1 and factor 2 were distinguishable from each other. Given some evidence for convergence and evidence for divergence of individual factors, items that loaded on factor 1 were extracted to represent novelty-seeking orientation in the structural equation model.

Table 4.24.Values of AVE, MSV, ASV and CR and covariance between factors of a two- factor model of cognitive style

Factor	Measures				Standardized Covariance	
	AVE	MSV	ASV	CR	Factor 1	Factor 2
Factor 1	0.36	0.24	0.24	0.86	1	
Factor 2	0.34	0.24	0.24	0.85	0.49	1

4.5.4. Observed measures

Observed measures of GPA and major are presented in Table 4.2. As seen from Table 4.2, GPA of participants ranged from 0.8-4.0. The mean GPA of participants was 3.2. The number of participants coded into major 1-5 was 169, 37, 57, 25, and 73, respectively.

The mean novelty scores of participants are presented in Figure 4.5. As seen from Figure 4.5, while some participants generated low novelty solutions, others could generate multiple novel solutions. As evident from the flatness of trend line at various points for mean novelty score in Figure 4.5, many participants showed the same novelty in their solutions.

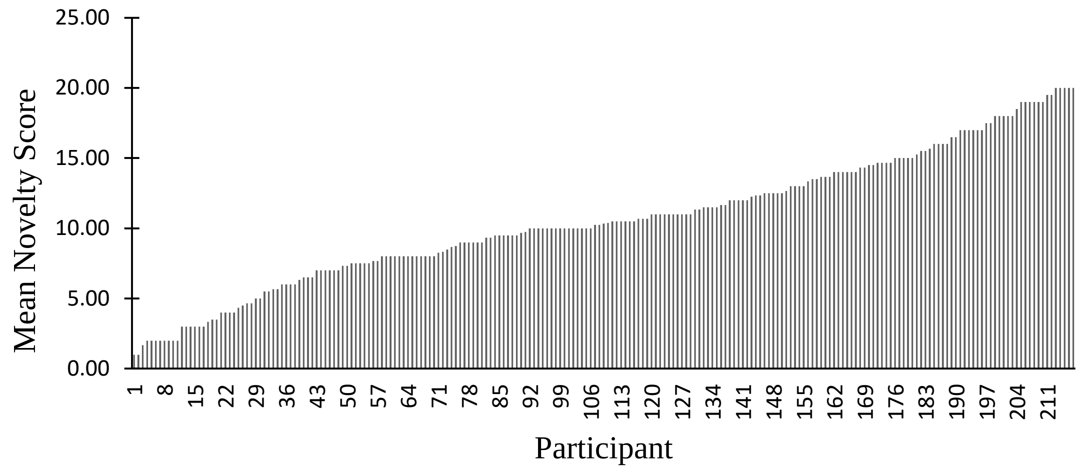

Figure 4.5. Distribution of mean novelty score of study participants.

4.5.5. Structural equation model

Results from the structural equation modeling suggested that the measurement model fits the data. The Chi Square fit index of 1.4 (df = 530) was within the acceptable threshold of 3. While the CFI value 0.86 was lower than the traditional.ly acceptable, but higher than the sometimes permissible, values, both the RMSEA and SRMR values were within acceptable ranges. The RMSEA and SRMR values were 0.04 and 0.06, respectively. Estimates of standardized factor loadings, standard errors, and their significance are presented in Table 4.25. As seen from Table 4.25, all items loaded significantly on their respective factors at a p value of 0.5. Factor correlations among

Table 4.25. Loading estimates, standard errors (Std.Err), loading significance (P(>abs(z)) and confidence intervals (ci.lower, ci.upper), and standardized loading estimates (Std. all) for manifest variables in the SEM model

	Estimate	Std.Err	z-value	P(>|z|)	ci.lower	ci.upper	Std.all
STR							
TD3	0.53	0.10	5.33	0.00	0.34	0.73	0.46
TD4	0.71	0.09	7.66	0.00	0.53	0.89	0.75
TD5	0.78	0.10	7.94	0.00	0.59	0.98	0.66
TD7	0.15	0.07	2.09	0.04	0.01	0.30	0.17
COM							
TD9	0.18	0.08	2.26	0.02	0.02	0.33	0.18
TD10	0.76	0.07	11.34	0.00	0.63	0.89	0.79
TD11	0.84	0.05	15.51	0.00	0.73	0.94	0.86
TD12	0.34	0.08	4.11	0.00	0.18	0.50	0.30
TD13	0.52	0.07	7.21	0.00	0.38	0.66	0.55
TD14	0.49	0.07	6.77	0.00	0.35	0.63	0.46
NS							
CS15	0.50	0.07	6.91	0.00	0.36	0.65	0.50
CS16	0.64	0.06	10.07	0.00	0.51	0.76	0.67
CS18	0.52	0.07	7.56	0.00	0.39	0.66	0.50
CS19	0.56	0.07	7.54	0.00	0.41	0.71	0.53
CS20	0.38	0.06	5.86	0.00	0.25	0.50	0.41
CS21	0.62	0.07	8.37	0.00	0.48	0.77	0.59
CS22	0.73	0.07	10.35	0.00	0.59	0.86	0.66
CS23	0.43	0.06	7.29	0.00	0.32	0.55	0.54
CS24	0.38	0.07	5.79	0.00	0.25	0.51	0.41
CS25	0.32	0.07	4.86	0.00	0.19	0.44	0.35
CS26	0.66	0.06	11.46	0.00	0.55	0.77	0.70
AN							
TM3	0.96	0.12	7.93	0.00	0.72	1.19	0.53
TM6	1.61	0.13	12.41	0.00	1.35	1.86	0.87
TM9	1.30	0.14	9.66	0.00	1.04	1.57	0.68
IN							
TM4	1.13	0.10	11.57	0.00	0.94	1.32	0.76
TM5	1.02	0.12	8.89	0.00	0.79	1.24	0.78
TM12	1.10	0.13	8.47	0.00	0.84	1.35	0.63
CH							
TM7	0.87	0.13	6.49	0.00	0.60	1.13	0.68
TM11	0.92	0.14	6.79	0.00	0.65	1.19	0.71

latent constructs suggested constructs are distinguishable from each other (i.e., no multicollinearity). The factor correlation matrix is presented in Table 4.26. As seen in Table 4.26, all correlations are below the traditional.ly high value of 0.85. Given satisfactory performance of the hypothesized measurement model, the hypothesized model formed the basis for structural modeling.

Table 4.26. Standardized correlations (* = significant value at $p < 0.05$) among manifest variables in the SEM model

	STR	COM	CH	AN	IN	NS
STR	1					
COM	0.60*	1				
CH	-0.04	-0.05	1			
AN	0.25*	0.22*	0.15	1		
IN	0.02	-0.11	0.79*	-0.02	1	
NS	-0.07	-0.12	0.07	-0.32*	0.20*	1

The correlation matrix in Table 4.26 shows relationships among manifest variables. A statistical.ly significant and positive correlation was observed between design task structuredness and complexity and between design task structuredness and task-related anxiety. The correlation between structuredness and complexity, however, was more than twice the correlation between structuredness and anxiety. A statistically significant and positive correlation was al.so observed between design task complexity and anxiety. The magnitude of correlation between complexity and anxiety was like the correlation between structuredness and anxiety. The correlation between challenge and interest was both statistical.ly significant and the highest in magnitude among all observed correlations. The negative correlation between anxiety and novelty-seeking orientation was also statistically significant and similar in magnitude to correlations between anxiety and other manifest variables. In other words, high novelty-seeking orientation is observed with lower anxiety levels. Interest was correlated positively to novelty-seeking orientation. While the remaining correlations among manifest variables were not statistically significant, data suggests positive and negative trends among constructs. For example, challenge is correlated negatively to both structuredness and complexity of a design task. Challenge and anxiety are correlated positively; higher the perceived challenge of a task, greater is the anxiety felt towards the task.

Regression analysis indicated a statistically significant positive correlation of 0.27 between design task structuredness and novelty (p value = 0.10) and a statistically significant negative correlation of 0.31 between complexity and novelty (p value of 0.05) after controlling for students' major, GPA, perception of task challenge, task-related anxiety, interest in task and novelty-seeking orientation. Only the association between complexity and novelty was found to have small practical significance. Although not practically significant, of the covariates, only one category of major (major 2 = BAEN, BMEN, CHEN, NUEN, OCEN, PETE) was found to be statistically different (r = -0.19) from undeclared students at a p value of 0.01. Estimates of coefficients in the regression model are presented in Table 4.27.

Table 4.27. Estimates of coefficients in the regression model. STR = structuredness. COM = complexity. AN = anxiety. IN = interest. CH = challenge. NS = novelty-seeking orientation.

	Estimate	Std.Err	z-value	P(>|z|)	ci.lower	ci.upper	Std.all
Novelty ~							
Major1	-0.55	0.79	-0.71	0.48	-2.09	0.99	-0.06
Major2	-2.65	1.04	-2.56	0.01	-4.68	-0.62	-0.19
Major3	-0.68	0.96	-0.71	0.48	-2.55	1.19	-0.06
Major4	-1.07	1.09	-0.98	0.33	-3.21	1.07	-0.06
GPA	0.21	0.53	0.40	0.69	-0.82	1.24	0.02
STR	1.27	0.71	1.79	0.07	-0.12	2.65	0.27
COM	-1.45	0.60	-2.41	0.02	-2.62	-0.27	-0.31
AN	0.20	0.45	0.45	0.65	-0.68	1.09	0.04
IN	-1.55	1.18	-1.32	0.19	-3.87	0.76	-0.33
CH	1.69	1.24	1.36	0.17	-0.74	4.12	0.36
NS	0.01	0.41	0.01	0.99	-0.79	0.80	0.00

4.5.6. Limitations

The results from this study are limited by the research methodology. First, the study design was limited by the choice of definitions and validity and reliability of the instruments. The validity and reliability of the instruments were somewhat compromised due to item quality, small number of items measuring a construct and/or the size of the available sample. Second, data collection was limited by data from a single institution, use of a single design task to obtain ratings on instruments, self-selection of participants, and time to complete the brainstorming activity. Limitations on data collection restrict generalizability of findings. Third, data analysis was limited due to lost information when missing observations were substituted by variable medians and categories of participant demographics were collapsed to achieve near-thirty observations for each cell size. In addition, the validity of the categories of qualitative responses to the essay question was limited due to lack of triangulation with another researcher. Moreover, data analysis was limited by use of linear regression analysis as the research method. Effects may be underestimated for predictors with a non-linear response and a small sample size. Nonetheless, the results provide insights in the discussion section about direct effects of design task structuredness and complexity on novelty after controlling for covariates.

4.6. Discussion

This study examined direct relationships between design task structuredness and novelty and complexity and novelty after controlling for covariates using the structural equation modeling approach. Covariates included students' GPA, major, perceived task challenge, interest in task, task-related anxiety, and novelty-seeking orientation. The preliminary model established presence of relationships between task structuredness and novelty and between task complexity and novelty. A statistically significant direct association was observed between engineering design task structuredness and novelty at a p-value of 0.1. As per the regression analysis, structuredness explained 7.30% of the variance in observed novelty scores. Like research in other domains (Reiter-Palmon, et al., 2009; Jo & Lee, 2012), a statistical.ly significant association was also observed between complexity and novelty at a p-value of 0.05. Complexity explained approximately 10% of the variance in novelty scores. Combined, the two design problem characteristics - structuredness and complexity - explained approximately 18% of the variance in observed novelty scores.

Further, findings about the direction of relationships between structuredness and novelty and between complexity and novelty suggested ways to support students' abilities to generate novel solutions to challenging design tasks. Findings indicated that the novelty of a solution increases with increases in structuredness of the design task. Novelty of a solution decreases with increases in complexity of the design task. While findings to support a positive, linear association between task structuredness and novelty were not found in previous research, the inverse relationship between task complexity and novelty found in present research is contrary to previous research (Reiter-Palmon, et al., 2009; Jo & Lee, 2012). The contradictory findings may be attributed to type of problem, participant backgrounds, or index used to measure creativity. Presence of a positive association between structuredness and complexity indicated that assigned design task may fall in the ill-structured and complex plane, and therefore, have a different result than everyday tasks (Reiter-Palmon, et al., 2009) that may fall in the well-structured and complex plane. Psychology students and IT company employees may behave differently (i.e., generate more novel solutions to complex tasks) than engineering students because of their backgrounds (e.g., approach to problem-solving, domain expertise, motivation). Different measures of creativity also give different results (Reiter-Palmon, et al., 2009). Nonetheless, present findings suggest discovery of strategies which engineering students can use to structure ill-structured tasks and break down complex tasks to improve novelty of solutions to similar design tasks.

In addition to offering insights about direct effects of structuredness and complexity of an engineering design task on novelty, present research provided information about covariates included in the model. Findings suggested examination of roles of disciplinary expertise (e.g., Nazzal, 2015) to support students' abilities to generate novel solutions. Like previous study (Nazzal, 2015), students' major (category 2 in present research) was found to be a statistically significant covariate at a p-value of 0.05. Major 2 (BAEN, BMEN, CHEN, ETID, ISEN, NUEN, OCEN and PETE) explained about 3% of the variance in novelty of solutions. Further, findings suggested that acquisition of disciplinary knowledge, especial.ly in BAEN, BMEN, CHEN, ETID, ISEN, NUEN, OCEN and PETE majors, may be disadvantageous to generating novel solutions when assigned with similar design tasks. Findings indicated mean novelty scores of undeclared majors were significantly different and higher than the mean novelty scorers of BAEN, BMEN, CHEN, ETID, ISEN, NUEN, OCEN and PETE majors. The present finding is consistent with previous work (Rathore, unpublished) which found the same majors generate conventional solutions compared to undeclared majors using a different statistical method. Lower mean novelty of scores with disciplinary knowledge in present study may be attributed to differences in exposure to design thinking/curriculum or design fixation (Smith & Linsey, 2011). These findings support further exploration of impacts of disciplinary knowledge/major on students' abilities to generate novel solutions to challenging design tasks. Such findings can inform engineering programs and book publishers about strategies to develop students' abilities to innovate solutions to challenging design problems.

Though no direct associations were observed between other covariates and novelty, previous research (Rathore, unpublished; Jo, et al., 2012, Fruend, et al., 2011, Martinsen, et al., 2000) indicated that covariates such as students' GPA, perceived task challenge, interest in task, task-related anxiety, and novelty-seeking orientation are significant predictors of novelty. The discrepancy in findings between the present and previous studies points to need for either transformation or representation of non-linear variables (e.g., anxiety) in code prior to running a SEM analysis and/or consideration of non-significant student characteristics as mediating or moderating variables in the SEM analysis. Possibilities of indirect associations are not precluded in future analysis since design task structuredness, complexity, and major explained only about 21% of the total variance in observed novelty. Findings support needs to develop empirical models that explain relationships between design problem characteristics and creativity as moderated and/or mediated by student characteristics, to understand the roles of learning activities and student characteristics for developing strategies to foster students' abilities to generate creative solutions to challenging design tasks.

Last, present research suggested consideration of confounding effects of problem and student characteristics on observed novelty similar to suggested by (Rodriguez, Mendoza, Gonzalez, Hernandez, Okudan, & Schmidt, 2011) to avoid drawing bias into conclusions comparing advantages of different ideation techniques. Combined, select problem and student characteristics accounted for approximately 21% of the total variance in observed novelty in this study. If variance from problem characteristics and/or student characteristics is left unaccounted for in design studies, effectiveness of ideation methods may be overestimated in comparative analyses and/or meta-analyses. Therefore, research studies should either hold problem and student characteristics constant or attribute related variability to problem and student characteristics when explaining variance of observed novelty due to ideation methods.

4.7. Conclusion

Conflicting claims about roles of engineering curricula in developing students' abilities to innovate solutions to design problems warranted further study about influences of learning activities on students' abilities to innovatively solve challenging design problems. The present study examined relationships of design task structuredness and complexity to novelty of solutions after controlling for students' GPA, major, perceived task challenge, task-related anxiety, interest in task and novelty-seeking orientation. A prospective, survey research design was used to collect data from a sample of engineering students at Texas A&M University. Relationships of structuredness and complexity to novelty of solutions were estimated from a causal model using a structural equation modeling approach. While a significant positive and a linear association were observed between design task structuredness and novelty, a significant negative association was observed between design task complexity and novelty. A statistical.ly significant correlation was found between structuredness and complexity. Of all the covariates, only the association between major 2 (BAEN, BMEN, CHEN, ETID, ISEN, NUEN, OCEN or PETE) and novelty was statistically significant relative to undeclared majors. Combined, structuredness, complexity, enrollment in major 2 explained approximately 21% of the total variance in novelty. Findings from this study suggest discovery of strategies which engineering students can use to structure ill-structured tasks and break down complex tasks to improve novelty of solutions to similar design tasks. In addition, it suggests exploration of impacts of disciplinary knowledge/major on students' abilities to generate novel solutions to challenging design tasks. Further, present findings support the need for further research on relationships between design problem characteristics and creativity as moderated and/or mediated by student characteristics, to understand the roles of learning activities and student characteristics and develop strategies for fostering students' abilities to generate creative solutions to challenging design tasks. Last, the study indicates that research on ideation should consider effects of problem and student characteristics on observed novelty to avoid drawing bias into conclusions when comparing advantages and disadvantages of different ideation techniques.

5. SUMMARY AND CONCLUSIONS

5.1. Summary

Preparing engineering students with abilities to provide innovative solutions to increasingly challenging design problems is essential to their success as engineers. Conflicting claims (Atman, et al., 1999; Cross, et al., 1994; Lai, et al., 2008; Genco, et al., 2012) about students' abilities to innovate solutions as they progress through the engineering curricula, however, warranted clarification of roles of instructor-assigned design tasks on students' abilities to generate innovative solutions to design tasks after controlling for effects of students' characteristics such as domain-relevant skills, cognitive style and task motivation (Amabile, 2013). Previous research on relationships between task characteristics and innovative solutions is limited (Reiter-Palmon, et al., 2009 and Jo, et al., 2012). Current research contributed to the literature by examining relationships between design task characteristics and abilities to innovate with a design task, a more encompassing definition of design task characteristics than previous research, a creativity measure specific to the domain of engineering (Sarkar, et al., 2011) and control variables and population unexamined in previous research.

Three manuscripts were developed to accomplish the research objective using survey data from a sample of 361 undergraduate engineering students enrolled at Texas A&M University. Students self-reported their perceptions of design task difficulty, domain-relevant skills, cognitive style, and task motivation. They brainstormed solutions to a design task, which required generation of ideas to separate paper and plastic from a mixed waste collection, for 10 minutes. Innovative abilities were represented using novelty (Sarkar, et al., 2011). Novelty was estimated from students' solutions to a design task based on rarity of solutions found in the sample.

5.1.1. First manuscript

Section 2 clarified the quality of measures of design task and student characteristics. Specifically, psychometric properties of measures of task difficulty, cognitive style, and current achievement motivation were examined using confirmatory factor and exploratory factor analyses and reliability analyses. The evaluation of measures was essential to determine their usability for research on engineering students' abilities to innovate solutions to engineering design problems.

Measures of task difficulty, current achievement motivation, and cognitive style were found to have weak validity and reliability. Fit indices obtained from the CFA did not support a well-fitting two-factor and four-factor model for task difficulty and current achievement motivation, respectively; however, an acceptable three-factor model was achieved for cognitive style. Further analysis, however, indicated that the cognitive style model did not achieve convergent and divergent validity. EFA supported presence of a two-factor model of task difficulty, a two-factor model of current achievement motivation, and a three-factor model of cognitive style. However, the resulting factor structures had issues such as non-loading items, cross-loading items, and poor internal consistency estimates.

Evaluation of psychometric properties of measures of task difficulty, current achievement motivation and cognitive style confirmed that factor structured obtained from the literature did not hold when a sample of undergraduate engineering students rated their perceptions of task difficulty, current achievement motivation, and cognitive style for an engineering design task. Further, the factor structures obtained from the EFA in this research were not supported by their respective theories. Current research attributed failures to support previous research on poor item quality, small number of observed measures, errors in coding of items, and/or small sample size. In addition, it supported needs to conduct additional research studies to further clarify use of measures of task difficulty, current achievement motivation and cognitive style in future research.

5.1.2. Second manuscript

Section 3 explored how engineering students' characteristics combined to predict observed novelty of their solutions to a design task. Specifically, the manuscript determined roles of GPA, classification, major, familiarity with a design task, current achievement motivation and cognitive style in predicting novelty of solutions to a design task using decision tree analysis. Characteristics such as an individual's domain expertise (estimated from GPA, classification, major, familiarity with design task), creativity-relevant skills (estimated from cognitive style), and motivation (estimated from current achievement motivation) have individual.ly been linked to creative performance in previous research (Amabile, 2013; Jo & Lee, 2012; Martinsen & Diseth, 2011). The exploration of roles of students' characteristics was essential. for determining and prioritizing the most important/significant characteristics for use as covariates - when studying the relationships between task difficulty and novelty using structural equation modeling– given the large number of measures, small sample size, and limited resources to collect additional data. In addition, moderating or mediating influences of students' characteristics were found from this analysis.

Decision tree analysis found GPA, major, current achievement motivation (facets: challenge, anxiety, interest, probability of success), and cognitive style (facets: novelty-seeking orientation, rules orientation) as significant predictors of observed novelty. Four combinations of students' characteristics resulted in rare solutions: (challenge > -2.498; range: [-4.30, 2.20]) and (anxiety > 1.943; range: [-2.09, 2.49]); (challenge >-2.498) and (anxiety < 1.943) and (GPA > 3.93; range: [0, 4.0]); (challenge > -2.498) and (anxiety < 1.943) and (GPA < 3.93) and (novelty-seeking orientation > -1.146; range: [-2.29, 2.49]) and (0.9332 < interest ≤ 1.162; range: [-3.49, 1.95]); (challenge > -2.498) and (anxiety < 1.943) and (GPA < 3.93) and (novelty-seeking orientation > -1.146) and (interest < 0.9332) and (major ≠ c or e; c = BAEN, BMEN, CHEN, NUEN, OCEN or PETE, e = ETID or ISEN).

Findings from the decision tree analysis were supported within the framework of Amabile's (2013) componential theory of creativity. As per Amabile's theory, a confluence of domain-relevant skills, creativity-relevant processes, motivation influences creative outcomes. The pruned tree suggested order of importance of confluence variables. The most significant to least significant variables are: challenge (facet of motivation), anxiety (facet of motivation), GPA (estimate of domain skills), novelty-seeking orientation (facet of creativity-relevant process), interest (facet of motivation), and major (estimate of domain skills). Moreover, while the researcher could not verify the hypotheses offered by Amabile (2013) due to methodological limitations, predictions about combinations for novel solutions found in this research were consistent with Amabile's projections. Overall, the pruned tree confirmed that a combination of domain-relevant skills, creativity-relevant processes, and task motivation influences creative outcomes.

Further, findings provided insights to for design studies regarding study control variables. Results indicated that studies must control for challenge, anxiety, GPA, novelty-seeking orientation, interest and major in design ideation studies to avoid drawing bias into conclusions about effectiveness of design ideation methods. However, studies must not dismiss variables that were not selected as significant/primary splitters in the decision tree until further analyses. It is possible that unimportant variables are secondary splitters (containing same information) that could not be tested in research with a complete dataset. It is also possible that a small sample size of various groups rendered significant variables unimportant in present analysis.

Last, findings in section 3 offer hypotheses that may be tested to develop instructional strategies to support novelty of solutions to a similar design task. For example, present research found conventional solutions were observed when few of the participants found the design task less challenging than the threshold value of challenge. Future research can test if novel solutions are observed when the same participants are assigned a more challenging design task (e.g., separate paper, plastic, and glass) than the assigned design task. Conventional solutions were al.so observed for the few low achievement participants who felt low anxiety towards a challenging task; however, they fell below the threshold value of novelty-seeking orientation. Future research can test if novel solutions are observed when the same participants are given a repertoire of strategies that develop their novelty-seeking orientation. Further, present research found that novel solutions were observed when participants' interest was held at an optimum level and/or they had the necessary disciplinary knowledge to solve the design task. Future research can explore instructional strategies to engage student interest and/or increase disciplinary knowledge to determine if novel solutions are observed for the conventional participants under instructional interventions. Additional studies with different design tasks and large sample size, however, are needed to test the stability of splitting variables and their thresholds for use in splitting students into different groups.

5.1.3. Third manuscript

Section 4 examined relationships between design task difficulty and novelty after establishing adequacy of measures and significance of covariates for this research. Specifically, the direct effects of engineering students' perceived structuredness and complexity of an engineering design task on novelty of solutions were determined using structural equation modeling. Controlled covariates included GPA, major, perceived task challenge, task-related anxiety, interest in task and novelty-seeking orientation. Findings explained relationships between design tasks and abilities to innovate as moderated or mediated by student characteristics, confounding effects of design tasks and students' characteristics for ideation studies and suggested discovery of strategies to develop students' abilities to innovate solutions.

Structural equation modeling indicated a significant positive linear association between design task structuredness and novelty, a significant negative association between design task complexity and novelty, and a statistically significant, positive correlation between structuredness and complexity. Of the covariates, only major 2 (BAEN, BMEN, CHEN, ETID, ISEN, NUEN, OCEN or PETE) was found statistically significant relative to undeclared majors. Combined, structuredness, complexity, enrollment in major 2 explained approximately 21% of the total variance in novelty.

The preliminary model used in this research established presence of relationships between task structuredness and novelty and task complexity and novelty. Though no direct associations were observed between covariates (except for major) and novelty, previous research (Rathore, unpublished; Jo, et al., 2012, Fruend, et al., 2011, Martinsen, et al., 2000) indicated that covariates such as students' GPA, perceived task challenge, interest in task, task-related anxiety, and novelty-seeking orientation are significant predictors of novelty. In addition, possibilities of indirect associations are not precluded in future analysis since design task structuredness, complexity, and major explained only about 21% of the total variance in observed novelty. These findings support needs to further develop empirical models that explain relationships between design problem characteristics and creativity as moderated and/or mediated by student characteristics, to understand the roles of learning activities and student characteristics to develop strategies for fostering students' abilities to generate creative solutions to challenging design tasks.

Moreover, research conducted in section 4 also suggested design researchers account for confounding effects of problem characteristics and student characteristics on observed novelty to avoid drawing bias into conclusions when comparing advantages and disadvantages of different ideation techniques using design tasks similar to the one used in present research. Findings indicated that two design problem characteristics - structuredness and complexity - explained approximately 18% of the variance in observed novelty scores. Student characteristics such as major 2 explained about 3% of the variance in novelty. If variance from problem characteristics and/or student characteristics is left unaccounted for in studies, effectiveness of ideation methods may be overestimated in comparative analyses and/or meta-analyses. Therefore, problem and student characteristics should either be held constant or effects attributed to when explaining variance of observed novelty due to ideation methods.

Further, present research provides information about conditions needed to support students' abilities to generate novel solutions to challenging design tasks. Findings indicated more structured the design task is, more novel is the solution. More complex the design task is, less novel is the solution. While findings to support the positive association between task structuredness and novelty were not found in previous research, the inverse relationship between task complexity and novelty found in present research is contrary to previous research (Reiter-Palmon, et al., 2009; Jo & Lee, 2012). The contradictory findings may be attributed to type of problem, study demographics, or index used to measure creativity. Nonetheless, present findings suggest discovery of strategies which engineering students can use to structure ill-structured tasks and break down complex tasks to improve novelty of solutions to similar design tasks.

In addition, findings suggest that acquisition of disciplinary knowledge, especial.ly in BAEN, BMEN, CHEN, ETID, ISEN, NUEN, OCEN and PETE majors, may be disadvantageous to generating novel solutions when assigned with similar design tasks. Findings indicated mean novelty scores of undeclared majors were significantly different and higher than the mean novelty scorers of BAEN, BMEN, CHEN, ETID, ISEN, NUEN, OCEN and PETE majors. Lower mean novelty of scores with disciplinary knowledge in present studies may be attributed to differences in exposure to design thinking/curriculum or design fixation. These findings support further exploration of impacts of disciplinary knowledge/major on students' abilities to generate novel solutions to challenging design tasks. Such findings can inform engineering faculty and book publishers about strategies that can be employed to develop students' abilities to innovate solutions to challenging design problems.

5.2. Combined contribution

This section compares and contrasts findings from the three manuscripts in three ways to illustrate their combined contributions. First, the validity and reliability of responses to scales of task difficulty, current achievement motivation, and cognitive style were established in the context of engineering education. Evaluation of task difficulty, current achievement motivation and cognitive style scales in manuscript #1 confirmed that scales were not supported by their respective theories when a sample of 180 undergraduate engineering students rated their perceptions of task difficulty, current achievement motivation, and cognitive style for an engineering design task. Research attributed failures to support previous research on poor item quality, small number of observed measures, errors in coding of items, and/or small sample size. However, when the same scales were re-evaluated after correcting coding mistakes and with a large sample size of 361 undergraduate engineering students in manuscript #2 and #3, the psychometric properties of scales improved significantly. The researcher obtained factor structures for each scale that were strongly supported by their respective theories. Construct validity and reliability of responses to measures also improved; nevertheless, similar to manuscript #1, research in manuscript #2 and #3 indicated needs for improved item quality and increases in number of items per measure to improve the overall psychometric properties of the task difficulty, current achievement motivation, and cognitive style scales.

Second, roles of students' characteristics such as GPA, classification, major, familiarity with a design task, current achievement motivation and cognitive style were clarified through manuscript #2 and #3. While manuscript #2 found GPA, major, current achievement motivation (facets: challenge, anxiety, interest, probability of success), and cognitive style (facets: novelty-seeking orientation, rules orientation) as significant predictors of observed novelty using a non-parametric decision tree analysis, research in manuscript #3 confirmed only one category of major as a significant predictor of observed novelty. Both studies confirmed that BAEN, BMEN, CHEN, NUEN, OCEN or PETE majors significantly underperform in novelty compared to undeclared majors. In addition to listed majors, decision tree analysis also found ETID and ISEN majors generate conventional solutions to design tasks. No association was found between other student characteristics and novelty in SEM analysis. The discrepancy in findings between the two studies points to need for either transformation or representation of non-linear variables (e.g., anxiety) in code prior to running a SEM analysis and/or consideration of non-significant student characteristics as mediating or moderating variables in the SEM analysis.

In addition, both manuscript #2 and #3 found needs for design researchers to control for confounding effects of students' characteristics and design tasks when examining effectiveness of ideation techniques. For example, in manuscript #2, results showed that challenge, anxiety, GPA, novelty-seeking orientation, interest and major significantly affect novelty of solutions. Results in manuscript #3 indicated that at least 21% of the variance in observed novelty is explained by two design task characteristics – structuredness and complexity – and students' major. If variance from problem characteristics and/or student characteristics is left unaccounted for in studies, effectiveness of ideation methods may be overestimated in comparative analyses and/or meta-analyses. Therefore, problem and student characteristics should either be held constant or effects attributed to when explaining variance of observed novelty due to ideation methods.

5.3. Conclusions

Conflicting claims about engineering students' abilities to innovate solutions to design tasks warranted evaluation of measures and clarification of roles of design task and student characteristics in developing innovative solutions. Three manuscripts clarified quality of measures and roles of design tasks and student characteristics using survey data from 361 students. The first manuscript evaluated measures of task difficulty, current achievement motivation and cognitive style using CFA, EFA and reliability analyses. Measures were found to have low validity and reliability. Future studies should be conducted with large sample sizes and improved item quality.

The second manuscript clarified roles of Grade Point Average (GPA), classification, major, task familiarity, current achievement motivation, and cognitive style in developing innovative solutions using decision tree analysis. GPA, major, current achievement motivation, and cognitive style were significant predictors of novelty. Four combinations resulted in rare solutions: (challenge > -2.498) and (anxiety > 1.943); (challenge >-2.498) and (anxiety < 1.943) and (GPA > 3.93); (challenge > -2.498) and (anxiety < 1.943) and (GPA < 3.93) and (novelty-seeking orientation > -1.146) and (0.9332 < interest ≤ 1.162); (challenge > -2.498) and (anxiety < 1.943) and (GPA < 3.93) and (novelty-seeking orientation > -1.146) and (interest < 0.9332) and (major ≠ c or e). Stability of predictors and cut-off values should be verified with different design tasks and large sample sizes.

The third manuscript examined relationships of design task structuredness and complexity to novelty of solutions after controlling for GPA, major, challenge, anxiety, interest and novelty-seeking orientation. Structural equation modeling found significant positive association between structuredness and novelty, significant negative association between complexity and novelty, and significant positive correlation between structuredness and complexity. Only major 2 (BAEN, BMEN, CHEN, ETID, ISEN, NUEN, OCEN or PETE) was found significant relative to undeclared majors. Structuredness, complexity, major 2 explained 21% of the total variance in novelty. Findings support development of models to explain relationships between design tasks and abilities to innovate as moderated or mediated by student characteristics, controlling confounding effects of design tasks and students' characteristics in ideation studies, and discovery of strategies to develop students' abilities to innovate solutions.

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APPENDIX A

Fourteen observed measures of task difficulty. Sub-scales: structuredness and complexity. Scale created with items from (Lee, 2014)

Measure	Description of observed measures
Structuredness	
TD1	Clearly stated goals or outcomes
TD2	Clearly defined criteria for successful problem solving
TD3	Clearly stated constraints that prevent successful problem solving
TD4	A single correct answer
TD5	A prescribed solution path
TD6	Requires solver to make assumptions and define the problem
TD7	Fal.ls within a predictable domain of knowledge
Complexity	
TD8	Exhibits the relationship between concepts and rules vaguely
TD9	Complex solutions to the problem
TD10	Confusion from inclusion of too many elements in the problem
TD11	Unclear coherence from presence of too many aspects
TD12	Inclusion of many concepts, rules and principles in the problem statement
TD13	Random combination of various aspects of the problem
TD14	Elements represented in too many ways

APPENDIX B

Twelve observed measures of task motivation. Sub-scales: probability of success, anxiety, interest, challenge. * = item reversed. Items from (Fruend, et al., 2011) listed here for instructive purposes only.

Measure	Description of observed measures
Probability of success	
TM1	I think I am up to the difficulty of this task.
TM2*	I probably won't manage to do this task.
TM10	I think everyone could do well on this task.
Anxiety	
TM3	I feel under pressure to do this task well.
TM6	I am afraid I will make a fool out of myself.
TM9	It would be embarrassing to fail at this task.
Interest	
TM4	After having read the instruction, the task seems to be very interesting to me.
TM8	For tasks like this I do not need a reward, they are lots of fun anyhow.
TM12	I would work on this task even in my free time.
Challenge	
TM5	I am eager to see how I will perform in this task.
TM7	I am really going to try as hard as I can on this task.
TM11	If I can do this task, I will feel proud of myself.

APPENDIX C

Thirty observed measures of cognitive style. Sub-scales: Rule orientation, Novelty seeking, and Planning. * = item reversed during analysis. Items from (Martinsen, et al., 2011) used for research and presented here for instructive purposes only.

Measure	Description of observed measures
Rule Orientation	
CS1*	I prefer detailed work which requires neatness and precision
CS2*	I prefer situation in which you have to stick to options that are tried and true
CS3*	I prefer to stick to what I know well
CS4*	I prefer to avoid major changes
CS5*	I work best in situation which are clear and straightforward
CS6*	I prefer situations in which you have to work according to specific rules
CS7*	I am best suited for work which requires precision and a systematic approach
CS8*	I prefer work with set routines
CS9*	I prefer to have clear guidelines to stick to in work
CS10*	I prefer to have systematic instruction when learning something new
CS11*	I am exceptionally precise and task-oriented in my work
CS12*	I mostly stick to accepted ideas
CS13*	I prefer to stick to a set plan when working or solving problems
CS14*	I most often try to use well-tried methods for solving problems
CS15*	When trying to solve a problem, I most often try to find new means of doing so
CS23*	I like situations in which you have to seek new knowledge actively
CS24*	I work best in complex situations
CS25*	I can change my opinions/ideas even if the situation does not require it
CS26*	I most like to investigate unchartered territory
CS30*	I prefer to plan and structure what I am to do
Novelty seeking	
CS12*	I mostly stick to accepted ideas
CS15*	When trying to solve a problem, I most often try to find new means of doing so
CS16	I quite like situations in which it is necessary to break with conventional. wisdom
CS17	I prefer to figure things out on my own when I am learning something new
CS18	I most often adopt a playful and curious approach to my work

Measure	Description of observed measures
CS19	I prefer to improvise in what I do
CS20	I bubble with ideas when I am solving problems
CS21	I most like situations in which you have to violate established norms
CS22	I most like to work with things I don’t know too well from before
CS23*	I like situations in which you have to seek new knowledge actively
CS24*	I work best in complex situations
CS25*	I can change my opinions/ideas even if the situation does not require it
CS26*	I most like to investigate unchartered territory
CS27	I like best to work with without a prearranged plan
CS29	I prefer working without any clear guidelines
Planning	
CS1*	I prefer detailed work which requires neatness and precision
CS7*	I am best suited for work which requires precision and a systematic approach
CS11*	I am exceptionally precise and task-oriented in my work
CS13*	I prefer to stick to a set plan when working or solving problems.
CS19	I prefer to improvise in what I do
CS23*	I like situations in which you have to seek new knowledge actively
CS25*	I can change my opinions/ideas even if the situation does not require it
CS27	I like best to work with without a prearranged plan
CS28	I often try things out without planning systematical.ly
CS29	I prefer working without any clear guidelines
CS30*	I prefer to plan and structure what I am to do