

**Exploring Novice Engineers' Mental Models of Collaboration and Engineering Design**

by

Rebecca L. Edwards  
B. Sci., Tufts University, 2009

A Thesis Submitted in Partial Fulfillment  
of the Requirements for the Degree of

MASTER of ARTS

in the Department of Educational Psychology and Leadership Studies

© Rebecca Edwards, 2018  
University of Victoria

All rights reserved. This thesis may not be reproduced in whole or in part, by photocopy or other means, without the permission of the author.

## **Supervisory Committee**

Exploring Novice Engineers' Mental Models of Collaboration and Engineering Design

by

Rebecca L. Edwards  
B. Sci., Tufts University, 2009

### **Supervisory Committee**

Dr. Allyson Hadwin, Department of Educational Psychology and Leadership Studies  
**Supervisor**

Dr. Todd Milford, Department of Curriculum and Instruction  
**Outside Member**

Dr. Peter Wild, Department of Mechanical Engineering  
**Outside Member**

## Abstract

Engineering educators have called for research on how best to foster and assess the development of collaborative expertise, particularly around engineering design. Mental models are internal representations depicting understanding. The quality of mental models and their similarity amongst group members have been found to influence performance and group processes in a range of disciplines: For example, flight, military, medical, and business teams. The purpose of this thesis was to examine three attributes (content, structure, within-group similarity) of the mental models of first-year undergraduate engineering students hold about both collaboration and engineering design in the context of a course-based engineering design project. Participants were 251 undergraduate engineering students enrolled in a first-year engineering course. Mental models were measured using relatedness ratings. This exploratory study drew upon network analysis indices and used descriptive, correlational, and comparative statistical techniques. Findings indicate (a) monitoring was viewed as the least central collaborative idea represented in the engineering students' mental models, (b) quality or expertise is indicated by the level of connection pruning in students' mental models, (c) performance and the quality of mental models of collaboration are associated, and (d) within-group collaborative mental model compatibility was more related to performance than mental model overlap. This study contributes to engineering education by suggesting mental models of the collaborative process are an essential factor to consider when preparing undergraduate engineering students to engage in collaborative engineering design.

*Keywords:* collaboration, engineering design, mental models, engineering education, collaborative learning

## Table of Contents

Supervisory Committee .....	iii
Abstract .....	iii
Table of Contents .....	iv
List of Tables .....	v
List of Figures .....	vii
Acknowledgments .....	viii
Chapter 1: Introduction .....	1
Chapter 2: Literature Review .....	3
Successful Collaboration .....	3
Supporting Successful Collaboration .....	5
Mental Models .....	7
Mental Models in Collaborative Learning .....	12
Purpose and Research Questions .....	19
Chapter 3: Methods .....	21
Research Design .....	21
Participants and Sampling Strategy .....	21
Research Ethics .....	22
Research Context .....	22
Procedure .....	22
Measures .....	23
Explanation of Network Analysis Techniques and Indices .....	28
Chapter 4: Results .....	38
Data Screening .....	38
Part 1: Collaboration Results .....	38
Part 2: Engineering design .....	49
Chapter 5: Discussion .....	60
What does the centrality of ideas reveal about novice engineers' mental models? [RQ1] .....	60
What does mental model structure reveal about novice engineers' mental models? [RQ2] ..	63
Does within-group mental model similarity relate to group performance grades? [RQ3] .....	66
Opportunities for Future Research .....	68
Implications for theory, research, and practice .....	71
Conclusion .....	75
References .....	78
Appendix A: Participant Consent Form .....	95
Appendix B: Mental Model Reflection Tool .....	98
Appendix C: Ethics Certification .....	105

### List of Tables

Table 1. <i>Within-Group Descriptive Statistics for Task Performance Measures (percentages)</i> .....	25
Table 2. <i>Collaboration Items</i> .....	26
Table 3. <i>Engineering Design Items</i> .....	28
Table 4. <i>Example of Compatibility (Intragroup agreement on Node Degree)</i> .....	37
Table 5. <i>Means, Standard Dev., and Confidence Intervals for Collaborative Node Degree</i> .....	39
Table 6. <i>Statistically Significant Mean Differences Between Collaborative Node Degrees</i> .....	40
Table 7. <i>Means and Standard Dev. for Collaborative Node Degree by Performance Group</i> .....	41
Table 8. <i>Results of Mixed-ANOVA Examining Collaborative Centrality Between Performance Groups</i> .....	42
Table 9. <i>Final Project Grade Descriptive Statistics for Collaborative Clusters</i> .....	44
Table 10. <i>Within Cluster Means, Standard Deviations, and Confidence Intervals for Collaborative Node Degrees, and Example Pfnets</i> .....	45
Table 11. <i>Results of MANOVA Examining Relationships Between Collaborative Clusters and Network Indices</i> .....	46
Table 12. <i>Chi-Squared Analysis of Collaborative Cluster Membership Among Performance Level</i> .....	47
Table 13. <i>Pearson Correlations, Means, and Standard Deviations: Collaborative Mental Model Within-Group Overlap and Group Task Performance Measures</i> .....	48
Table 14. <i>Correlations, Means, and Standard Deviations for Intragroup Agreement on Collaborative Node Degree and Group Task Performance Measures</i> .....	49
Table 15. <i>Means, Standard Dev., and Confidence Intervals for Engineering Design Node Degree</i> .....	50
Table 16. <i>Statistically Significant Mean Differences Between Engineering Design Node Degrees</i> .....	50
Table 17. <i>Means and Standard Dev. for Engineering Design Node Degree</i> .....	51
Table 18. <i>Results of Mixed-ANOVA Examining Engineering Design Centrality Between Performance Groups</i> .....	52
Table 19. <i>Final Project Grades Descriptive Statistics for Engineering Design Clusters</i> .....	54
Table 20. <i>Within Cluster Means, Standard Deviations, and Confidence Intervals for Engineering Design Node Degrees, and Example Pfnets</i> .....	54
Table 21. <i>Results of MANOVAs Examining Relationships Between Engineering Design Clusters and Network Indices</i> .....	58
Table 22. <i>Games Howell Post Hoc Tests for Engineering Design MANOVA</i> .....	58
Table 23. <i>Chi-Squared Analysis of Engineering Design Cluster Membership Among Performance Level</i> .....	59
Table 24. <i>Pearson Correlations, Means, and Standard Deviations: Engineering Design Mental Model Within-Group Overlap and Group Task Performance Measures</i> .....	60
Table 25. <i>Correlations, Means, and Standard Deviations for Intragroup agreement on Engineering Design Node Degree and Group Task Performance Measures</i> .....	59

### List of Figures

<i>Figure 1.</i> Example demonstrating the content/structure of a movie theatre mental model. ....	13
<i>Figure 2.</i> Three examples demonstrating the similarity of mental models of a movie theatre. .	13
<i>Figure 3.</i> Histogram of the three performance groups. ....	24
<i>Figure 4.</i> Collaboration mental model instrument. ....	26
<i>Figure 5.</i> Scale for relatedness rankings. ....	27
<i>Figure 6.</i> Engineering design mental model instrument. ....	28
<i>Figure 7.</i> Example of a network with five nodes and seven edges.....	29
<i>Figure 8.</i> Process used to derive pfnets. ....	31
<i>Figure 9.</i> Four sample networks and their corresponding network indices.....	32
<i>Figure 10.</i> Overlap for five comparison networks. ....	35
<i>Figure 11.</i> Collaboration cluster analysis scree plot. ....	43
<i>Figure 12.</i> Collaboration cluster analysis dendrogram. ....	43
<i>Figure 13.</i> Engineering design cluster analysis scree plot. ....	53
<i>Figure 14.</i> Engineering design cluster analysis dendrogram. ....	53
<i>Figure 15.</i> Examples of a highly pruned mental model and an unpruned mental model.....	66

## Acknowledgments

This thesis was supported by an Insight Grant awarded to A. F. Hadwin and P. H. Winne from the Social Sciences and Humanities Research Council of Canada (435- 2012- 0529), a Chair in Design Engineering Grant awarded to P. Wild from the Natural Sciences and Engineering Research Council of Canada (CDEPJ 335088), and a SSHRC Joseph-Armand Bombardier Master's Scholarship awarded to R. L. Edwards. I want to acknowledge and thank: Dr. Hadwin for providing me with an academic home, her endless support through this process, and the many opportunities she made possible; Dr. Milford for spreading the joy of statistics; Dr. Wild for acting as a bridge into the world of engineering; the TIE lab for sharing tears, chips, and lunchtime walks; the TIL team for the flexibility to make this thesis happen; my family and friends for trusting that I would finish in my own time; and, my partner for everything he is and does. Throughout this process I have found support in so many places, I want to thank everyone for helping me along the way.

## Chapter 1: Introduction

Collaboration is “coordinated, synchronous activity that is the result of a continued attempt to construct and maintain a shared conception of a problem” (Roschelle & Teasley, 1995, p. 70). The terms teamwork and collaboration are often used interchangeably. Employers have consistently cited collaboration or teamwork as one of the top three skills needed by new entrants into the workforce (Casner-Lotto, 2006; Hart Research, 2015). Due to the growing need for collaborative expertise, Canada has identified collaboration as an essential workplace skill and a critical 21st-century competency (Employment and Social Development Canada, 2015; Premier's Technology Council of BC, 2010). In response to this societal trend, post-secondary institutions have prioritized the development of collaborative skills to meet changing workforce demands. For example, the University of Victoria has listed “collaboration and the ability to work in teams” as an institution-wide undergraduate learning outcome (University of Victoria Calendar, 2016, p.676).

While a focus on collaborative work is apparent across disciplines, this focus is particularly noticeable in courses where students learn engineering design. Teamwork is an integral component of the engineering design process (Dym, Agogino, Eris, Frey & Leifer, 2005). Bucciarelli (1994) described the engineering design process as “a social process of negotiation and consensus, a consensus somewhat awkwardly expressed in the final product” (p. 21). Furthermore, early career engineers have identified teamwork as one of the most important Accreditation Board for Engineering and Technology (ABET) competencies (Passow, 2012), and professional capabilities contributing to success (Scott & Yates, 2002). Collaboration and engineering design intersect; successful design depends on successful collaboration.

Engineering education programs must foster the ability to work in groups to receive accreditation because of the importance of collaboration to the discipline (Accreditation Board for Engineering and Technology, 2016; Canadian Engineering Accreditation Board, 2015). Collaborative engineering design projects are now a staple of engineering education programs (Dym et al., 2005). While engineering programs provide opportunities for students to collaborate, collaborative success and the acquisition of collaborative expertise are not guaranteed outcomes. When asked about their collaborative engineering design experiences, first-year engineering students have tended to report “working as a team” as their biggest challenge (Moazzen, Miller, Wild, Jackson, & Hadwin, 2014, p. 4). Furthermore, engineering design instructors reported “inexperience with working on large scale projects and working in teams” as a difficulty for first-year engineering students (McGuire, Li, & Gebali, 2015, p. 4).

Engineering educators have called for research on how best to foster and assess the development of collaborative expertise, particularly around engineering design work (Borrego, Karlin, McNair, & Beddoes, 2013; Shuman, Besterfield-Sacre, & McGourty, 2005). Moreover, Borrego et al. (2013) recommend the field of engineering borrow the rich teamwork knowledge developed in other disciplines and apply it to undergraduate engineering design groups. In response to this call, this thesis investigates the mental models students develop during the collaborative engineering design process. Furthermore, this investigation strives to contribute to a more extensive research project focused on assessing the teamwork, and engineering design knowledge and competencies of undergraduate engineering students.

## Chapter 2: Literature Review

### Successful Collaboration

Collaboration occurs when a group works in concert towards a shared objective (Dillenbourg, 1999), and collaboration is characterized by equality and mutual influence (Damon & Phelps, 1989; Johnson & Johnson, 1989). However, merely placing individuals together in groups or teams does not guarantee successful and productive collaboration (Barron, 2003; Dillenbourg, 1999 & 2002; Roschelle & Teasley, 1995). Successful collaboration occurs when five critical elements harmonize allowing individuals in a group to:

1. Work together towards a common objective (Dillenbourg, 1999).
2. Develop a shared understanding of what it is they need to do (Rochelle & Teasely, 1995).  
This awareness or acumen about what a task entails is called task understanding (Hadwin, 2006; Winne & Hadwin, 1998).
3. Draw on the resources (i.e., knowledge, skills, and ideas) of all individuals within the group (Johnson & Johnson, 1989; Roschelle & Teasley, 1995). This means collaborators are interdependent (Johnson & Johnson, 1989).
4. Co-construct knowledge artifacts which are not the sum of individual contributions, but rather a unique meaning formulated through working together (DiDonato, 2013; Johnson & Johnson, 1999; Miller, 2015; Roschelle & Teasley, 1995; Salas, Rosen, Burke, & Goodwin, 2009).
5. Work within a socially constructed joint problem space (Roschelle & Teasley, 1995). This problem space is not necessarily a physical place but is a conceptual space where

collaborators play out their interdependence (Dillenbourg, 1999; Roschelle & Teasley, 1995).

Consider the following example of a group playing in a collaborative escape room. An escape room is a live-action collaborative game where players are locked in a room and must work together to escape in under one hour.

*Three players are preparing to enter the room. As they wait to begin, they discuss the game. One player asks the others what to expect, and another player responds they will need to work together to escape the room. The players chat about this idea and then enter the room. In the room, the players talk about splitting up to work on different puzzles but decide they should stick together because they believe they need to share what they find.*

*After a few minutes, a player finds the first puzzle and tells the group the lock will open with a combination of five letters. All the group members look for a clue that will help them to open the lock. Eventually, a player notices there are five pictures in the room, but this player does not know how to use this clue. A different player, who has prior experience with word puzzles, suggests the pictures might form a type of acrostic – the first letters of the words represented by the pictures might spell out a word. The group banters back-and-forth with potential solutions, and finally, the lock opens. The players continue to explore the room and work together to solve the puzzles they discover.*

This example illustrates the five elements of successful collaboration. First, the collaborators had a common objective: to escape the room in under one hour. Second, the players developed shared task understanding. For example, outside the room, a player asked the others what to expect, sparking a conversation about what the task would entail. This conversation continued throughout the game. Third, the collaborators were interdependent. In the room they solved the first puzzle by drawing on the contributions and expertise of all the collaborators: one player discovered the puzzle, another player discovered the clue, and the third player suggested the solution. Fourth, the collaborators created a product that was more than the sum of individual contributions. The collaborators co-constructed knowledge and expertise, bantering back-and-forth, and only by intertwining their effort did the group solve the puzzle. Fifth, the players develop a joint problems space. In this game, the players worked in a physical space, but they also worked in a conceptual space where they used conversation to share ideas, information, prior knowledge, and skills.

### **Supporting Successful Collaboration**

To harmonize the five critical elements of collaboration, collaborators must engage in productive collaborative interactions. In other words, negotiate, combine and coordinate their on-going action. The regulation of learning is a fundamental element guiding or controlling this process (Järvelä & Hadwin, 2013). Regulation is a recursive process (Winne & Hadwin, 1998) embedded in both individual and group learning (Järvelä & Hadwin, 2013). It is apt to discuss the regulation of learning because learning is embedded in collaboration (Dillenbourg, 1999): Collaborators learn by co-constructing knowledge artifacts.

During regulation of learning individuals and groups monitor progress towards goals and make strategic adjustments to behaviour, cognition, motivation, and emotions (Hadwin, Järvelä, & Miller, 2011; Järvelä & Hadwin, 2013; Winne & Hadwin, 1998). Collaboration necessitates individuals to regulate themselves (self-regulation) and to regulate together as a group (socially-shared regulation; Hadwin et al., 2011; Hadwin, Järvelä, & Miller, 2017; Järvelä & Hadwin, 2013). Regulation at the individual level and at the group level interact and influence each other: The regulatory affordances and constraints created through this reciprocal relationship are the co-regulation of learning (Hadwin et al., 2017).

Several theoretical models of regulation exist (Boekaerts & Niemivirta, 2000; Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 1986; Zimmerman, 1989; Panadero, 2017). Central to most of these models is the idea that, during learning, individuals and groups move through the loosely sequenced phases of planning, enacting, and adapting (Puustinen & Pulkkinen, 2001; Winne and Hadwin, 1998; Zimmerman, 1986). Planning is critical because during this phase collaborators develop shared task understanding and common goals, these two elements become the basis for strategic action and metacognitive control (Hadwin, 2017; Winne, Hadwin, & Perry, 2013). Planning sets the stage for collaboration, but novice collaborators often neglect planning or report it as a challenge (Hadwin, 2017). Thus, research on planning is essential: By understanding effective and successful planning, educators and researchers can find ways to support collaboration.

Miller and colleagues (e.g., Miller, 2015; Miller & Hadwin, 2015; Miller, Hadwin, & Starcheski, 2017; Starcheski et al., 2017) have begun to explore the efficacy of supporting collaboration through scripting and visualizing task understanding. However, while task

understanding is critical to collaborative success, it is only a piece of the mental intuition guiding strategic engagement. Task understanding is embedded within more holistic visions of the situation.

Miller (2015) identifies “holistic ‘vision[s]’ of how the task can be successfully completed” as mental models (p. 17). Going back to the earlier example: before starting the escape game, the players’ task understanding included the ideas of ‘escape the room’ and ‘work together’. When asked what to expect, a player might verbalize ‘we need to work together to escape the room’. However, these ideas have more hidden meaning in the player’s mind. This hidden meaning is the *sense* of what the group needs to do; these *senses* are mental models. Task understanding is the part of a mental model pulled into human consciousness to comprehend a task, or metacognitive knowledge of the task (Hadwin & Winne, 1998; Miller, 2015;). While task understanding might play a particular role in conscious planning, the broader mental models also influence collaborative success by directing an individual’s or groups’ on-going action.

### **Mental Models**

It is critical to investigate the mental models that develop during successful (or poor) collaboration to better support collaboration. Hadwin et al. (2017) point out “researching regulation [of learning] also requires an understanding of the beliefs, self-perceptions, and mental models that shape and are shaped by ... [learner] actions and reactions over time and events” (p. 85). Furthermore, Borrego et al. (2013) suggest engineering educators could benefit from understanding the shared mental models students develop during collaborative engineering design projects and Badke-Shaub, Lauche, and Neuman (2007a) comment, “design seems to be an obvious field to study mental models” (p. 1).

While researchers have called for explorations of mental models of collaborative engineering design, few studies have conducted comprehensive investigations of these mental models. The existing research on mental models during collaborative engineering design has focused on the impact of mental model similarity within the team (e.g., Bierhals, Schuster, Kohler, & Badke-Schaub, 2007; Carley, 1997; Dong, Kliensmann, & Deken, 2008), the impact of mental model accuracy (e.g., Dong, et al., 2008), and the degree of mental model change over time (e.g., Lee & Johnson, 2008). Literature describing the content and structure of collaborative engineering design mental models is lacking. This thesis seeks to contribute to the collaborative learning literature and the engineering education literature by exploring the mental models held by undergraduate engineering students during a collaborative engineering design project.

**What are mental models?** Mental models are internal representations (memory structures) composed of knowledge, beliefs, and perceptions which will influence strategic engagement ( Craik, 1952; Derry, 1996; Johnson-Laird, 1983, 1989; Jones, Ross, Lynam, Perez, & Leitch, 2011; Klimoski & Mohammed, 1994; Mohammed, Klimoski, & Rentsch, 2000; Rook, 2013). The mind constructs these memory structures in an ad hoc manner; mental models are a form of schema which are not stored intact in memory, but rather constructed in situ (Al-Diban, 2012; Darabi, Nelson, & Seel, 2010; Derry, 1996; Seel, 2001).

**What types of mental models influence collaboration?** When discussing or researching mental models, it is useful to distinguish between types of mental models (Cannon-Bowers et al., 1993; Rasmussen, 1979; Rouse & Morris, 1986). Types of mental models are essentially clusters of information about particular aspects of the situation or task (Rouse & Morris, 1986). Miller and colleagues suggest conditions influencing collaborative action can be organized into three

broad classes: self-conditions, group-conditions, and task-conditions (Hadwin et al., 2017; Miller, 2015). This view of collaborative conditions creates a useful framework for classifying mental model types. Leading to three types of mental models: self, group, and task. This extends the ideas of researchers who have focused on mental models of teamwork and task work (e.g., Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000). As the current thesis strives to investigate the teamwork and engineering design knowledge of undergraduate engineering students, it focuses on mental models of the collaborative process and the engineering design process. The collaborative process is an aspect of the group mental model, and the engineering design process is an aspect of the task mental model.

***Collaborative process mental model.*** Mental models of collaboration focus on what people know, think and believe about collaborative work. Collaborative process mental models have been called teamwork mental models in the organizational psychology literature. Typical measures have included items related to socio-emotional climate, planning, coordination, roles and responsibilities, knowledge of teammates, and communication (e.g., Lim & Klein, 2006). At times, measures of teamwork mental models have included ideas which are not applicable to collaborative group work, even though these ideas are applicable to some forms of group work. For example, Lim and Klein (2006) include the item “team members accept decisions made by the leader” (p. 417). Collaborators have symmetry of status, action, and knowledge (Dillenbourg, 1999); Rather than taking orders from a more skillful other, collaborators – each with their own expertise – negotiate group decisions. The item used by Lim and Klein is inappropriate for a collaborative mental model measure. Thus, the collaborative process mental model measure

used in this thesis drew on themes from the teamwork literature but aligned items with theory and research on collaborative learning.

***Engineering design process mental model.*** Task work mental models are individual understandings of what the task is, the tools used for the task, and how to approach the task (i.e., task strategies). In a typical study, Edwards, Day, Arthur, & Bell (2006) included strategies such as “control ship speed and distance” and “change trajectory of ship” as items in their task work mental model measure (p. 730). Engineering design mental models are a special type of task work mental model. Mental models of engineering design focus on what people understand about the engineering design process. Although the engineering design process is a fundamental component of effective collaborative engineering design and engineering programs explicitly teach students models of the engineering design process, only a few studies have specifically investigated mental models of the engineering design process (e.g., Lee & Johnson, 2008). In this thesis, the engineering design process mental models measure included the major steps in the engineering design process: steps central to learning design in engineering.

**Why are mental models important during collaboration?** During collaboration, group members – each with their own unique mental models stemming from differing histories, ideas, and priorities – must work in tandem towards a single group objective. Even though mental models are internally held personal representations, each group member’s mental models are a collaborative condition influencing engagement at the individual level and the group level, and thus mental models influence the products of collaboration.

***Individual Level: My Strategic Engagement.*** Mental models are a condition influencing an individual’s strategic engagement. People form mental models in every situation, but people

are not necessarily aware their mental models exist (Johnson-Laird, 1989). While individuals might not be fully aware of their mental models, these models are personal theories influencing how an individual will act within a situation ( Craik, 1952; Rook, 2013). Thus, mental models direct an individual's strategic engagement within a task. By influencing individual strategic engagement, mental models also have an impact on the products of collaboration. There is little research investigating mental models during collaborative engineering design at the level of the individual group members; most research has aggregated individual mental models to the group level to investigate group similarity and group accuracy. This thesis will explore the mental models of collaboration and engineering design at the individual level. This thesis examines: (a) the characteristics of mental models individuals hold during collaboration, (b) the relationship between those mental models and task performance.

***Group Level: Our Coordination of Engagement.*** Mental models are a condition influencing a group's coordination of action or interdependence. A common theoretical assumption, in the teamwork literature, is groups who negotiate better shared mental models during collaboration will engage in the task in more congruent ways and tend to be more successful (e.g., Cannon-Bowers, Salas, & Converse, 1993). Additionally, in a review of teamwork challenges, Bakhtiar (2015) identified a lack of shared mental models as a difficulty often encountered during collaboration. For example, if two teammates have a similar understanding of how collaboration works they are less likely to be in conflict and more likely to exhibit compatible behaviour. Thus, at the group level, the degree of similarity of the mental models held by individual group members can either help or hinder the coordination of group level action.

Prior research from other fields suggest the level similarity of mental models held by the individuals within a group has a positive relationship to both the performance of the group (e.g., DeChurch & Mesmer-Magnus, 2010; Mohammed, Ferzandi, and Hamilton, 2010) and group processes (e.g., Van den Bossche, Gijsselaers, Segers, Woltjer, & Kirschner, 2011). While research on mental models at the group level during collaborative engineering design does exist, this body of research is still quite small and often focuses on simulations rather than real-world engineering design tasks (e.g., Dong et al., 2013). To contribute to this body of research, this thesis will explore mental models of collaborative engineering design at the group level. Specifically, this thesis examines the link between similarity of mental models and task performance.

### **Mental Models in Collaborative Learning**

During collaboration, mental models have three primary properties the idea units, structure, and similarity. First, mental models are composed of ideas sparked by the conditions of the situation (Derry, 1996; Rouse & Morris, 1996). Second, mental models have structure: the mind organizes ideas into a coherent understanding (Carley & Palmquist, 1992; DeChurch & Mesmer-Magnus, 2010; Klimoski & Mohammed, 1994). Figure 1 illustrates the concepts of mental model content and structure. In this example, the ideas units of 'movie', 'soda', 'popcorn', 'happy', and 'friends' are the content of this individual's mental model of a movie theatre, and the links between these ideas are the structure. Both the idea units contained in the mental model and the way these idea units are organized (the structure) influence how the mental model drives, or controls, on-going action (Carley and Palmquist, 1992, DeChurch & Mesmer-Magnus, 2010; Mohammed et al., 2010; Resick, Murase, Bedwell, Jiménez, and DeChurch, 2010).

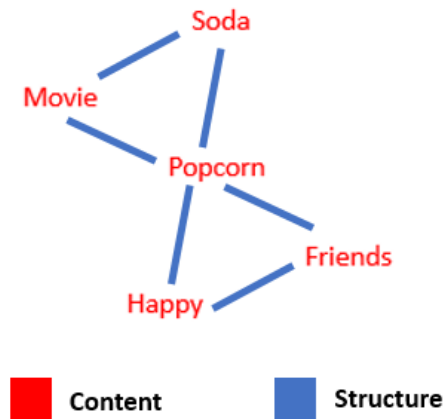


Figure 1. Example demonstrating the content and structure of a movie theatre mental model.

During group work, a third property is added to the mix: the mental models of individuals in the group share some degree of similarity. Figure 2 illustrates three different mental models of a movie theatre. The three models are similar but example one differs from (a) example two in content and (b) example three in structure. Theory and research suggest groups who share more similar mental models are on the same page and will be more in sync. This synchronicity affords higher quality team processes and team performance (Cannon-Bowers et al., 1993).

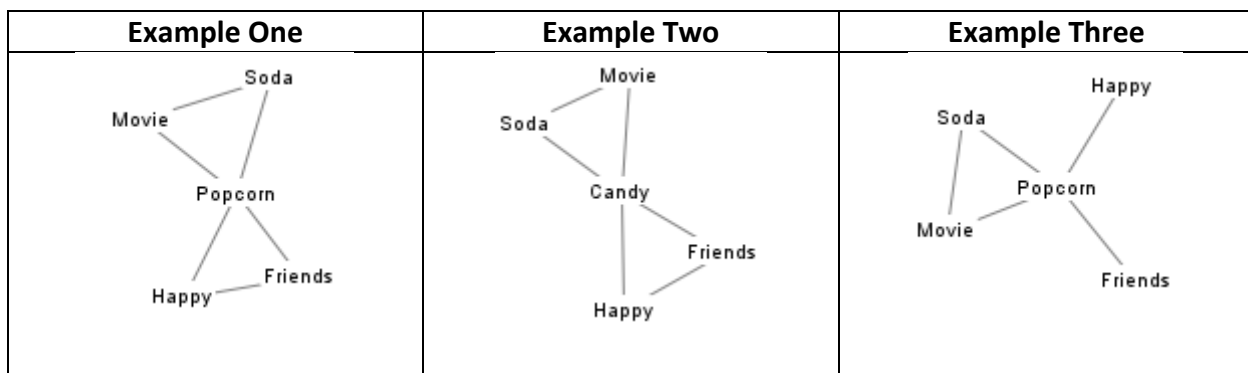


Figure 2. Three examples demonstrating the similarity of mental models of a movie theatre.

Much of the research on mental models held during group work has focused on the similarity between group members (e.g., Bergiel, Gainey, & Bergiel, 2015; Lim & Klein, 2006;

Santos & Passos, 2013). There has been a dearth of empirical investigations on the importance of the actual content and structure of mental models held during group work. This thesis will explore mental models of engineering design and collaboration on the individual level by investigating if aspects of mental model content and structure are related to collaborative success. Additionally, this thesis will explore mental models on the group level by testing if similarity between group members is related to collaborative success.

**Idea Units.** Mental models are composed of idea units, sometimes called memory objects, and idea units are the smallest form of memory schemata (Derry, 1996). An idea unit can be a piece of factual knowledge, a belief, or a perception (diSessa, 1983; Mohammed et al., 2000). Idea units are activated for use in a mental model, by the conditions or cues in the situation or task (Rouse & Morris, 1996). Conditions can arise from either external or internal sources (Winne, 1997). External conditions are those sources of information present in the physical world. For example, task instructions, ideas and perspectives shared by others, and even the physical configuration of the problem space. Internal conditions are the rich memory databases individuals develop/learn over time through personal or vicarious experiences. Hadwin et al. (2017) refer to these as “socio-historical databases”. The ideas contained within mental models will impact subsequent action or strategic engagement ( Craik, 1952; Hadwin et al., 2017; Rook, 2013) and, in this way, influence task performance.

While the literature has identified idea units as a critical property of mental models, little research has investigated mental models at this granularity. Based upon an exhaustive review of the literature, no research on collaborative or engineering design mental models has identified if individuals view particular idea units as more central to collaboration or engineering design.

This thesis will attempt to fill this gap by investigating the centrality of idea units within mental models of engineering design and collaboration: Are there particular ideas which are more central to mental models of engineering design and collaboration? Is idea centrality consistent across performance levels? Idea centrality will be measured as the degree of the node representing the idea unit.

**Measurement of idea units.** To understand an individual's mental model, it is valuable to examine the ideas, or content, contained within the mental model. Researchers have investigated the idea units contained within mental models in two ways: (a) asking participants to freely recall the content of their mental models (e.g., Jeong & Chi, 2007) or (b) providing participants with crucial content then asking participants to recognize how those ideas fit into their own mental models. Crucial content has been identified in various ways, such as by subject matter experts (e.g., Rowe & Cooke, 1995), through task analysis (e.g., Edwards et al., 2006), or from pilot testing (e.g., Langan-Fox, Code, & Langfield-Smith, 2000). There are problems with both free recall of content and providing content. Free recall makes it challenging to compare understandings across participants (Badke-Schaub, Neumann, Lauche, & Mohammed, 2007b). However, by providing content the researcher might tamper with their participants' mental models: the content might not have previously "existed in the minds" of the participants (Mohammed et al., 2010, p.12). Mental model researchers have tended towards providing participants with content because this methodology simplifies statistical comparisons between and within participants (Mohammed et al., 2000). Following the trend in the literature, the measurement technique used in this thesis will provide participants with ideas. The analysis will compare idea centrality across ideas and between performance levels.

**Structure.** The mind organizes idea units into coherent, usable mental models (de Kleer & Seely Brown, 1983; Derry, 1996). This organization, or structure, is built of the connections between idea units (Derry, 1996). Mental model structure differs across individuals. For example, evidence suggests experts have more elaborate and complex mental models than do novices (Al-Diban, 2012; Al-Diban & Ifenthaler, 2011). Several systematic reviews and meta-analyses on the mental models held during teamwork have highlighted the importance of measuring mental model structure (e.g., DeChurch & Mesmer-Magnus, 2010; Mohammed et al., 2000; Mohammed et al., 2010). Most research on mental models held during teamwork has used structural measures. However, research on the structure of mental models has focused on how an individual's structure differs over time (e.g., Jeong & Chi, 2007) or on the congruence or similarity of structure between teammates (e.g., Mathieu, et al., 2000). Little research has focused on describing the actual structure of mental models held during collaborative work.

An exception is Mathieu, Heffner, Goodwin, Cannon-Bowers, & Salas (2005) who did use profiles of the centrality of ideas contained within individual's mental models to assess the quality of their mental model structure. Mathieu et al. conducted a cluster analysis on the teamwork mental models of teamwork researchers (experts), using idea centralities as the clustering variables. Their results had a three-cluster solution. Participants in Cluster B "had the highest expertise scores" and "viewed the various team attributes as being moderately related to one another", and on average had pruned more than half of all possible structural links (p. 46). Additionally, Mathieu et al. used a discriminate analysis to assign novices into the three expert clusters, and then rated mental model quality based on cluster assignment. Those individuals assigned to Cluster B received the most points for their mental models. Team mental model

quality (aggregated from individual quality scores) was related to quality of team process and task performance. Building on the findings of Mathieu et al. (2005), this thesis will investigate the structure of mental models by describing the structure of emergent mental model clusters and identifying if particular clusters are associated with collaborative success. Additionally, this thesis will fill a gap in the literature by investigating the structure of engineering design process mental models. Mental model structure will be represented as the underlying network structure, and network indices will be used to describe this structure.

**Measurement of structure.** Useful measures ascertain mental model structure (Carley & Palmquist, 1992; DeChurch & Mesmer-Magnus, 2010). Researchers have measured the structure of mental models using concept mapping (e.g., Burtscher, Kolbe, Wacker, & Manser, 2011), card sorts (e.g., Smith-Jentsch, Cannon-Bowers, Tannenbaum, & Salas, 2008) and proximity data. Proximity data has been collected in a variety of ways, including relatedness rankings and textual analysis. Using relatedness rankings: proximity is the similarity of ideas as rated by participants (e.g., Stout, Cannon-Bowers, Salas, & Milanovich, 1999). Using textual analysis: proximity is the physical distance between relevant ideas (e.g., Van den Bossche et al., 2011). By far, the most common methodology used in the study of mental models has been relatedness rankings. Relatedness rankings allow researchers to use network analysis tools to extract mental model structure. This thesis will first measure mental model structure using relatedness rankings and then extract structure using the Pathfinder tool.

**Similarity.** Some types of cognitive diversity within an engineering design team may lead to better design results (Milliken, Bartel, & Kurtzberg, 2003). However, Badke-Schaub et al. (2007b) suggested, in an engineering design team "it seems essential that there is at least a

shared mental model of the team” and the “roles and responsibilities in the team” (p. 11). Research on the similarity of mental models within teams has focused on the connection between similarity and performance, and the connection between similarity and team processes (e.g., adaptation, collective efficacy, learning processes, coordination, cooperation, communication, conflict). The preponderance of evidence suggests teams who have more similar mental models tend to perform better; Mohammed et al. (2010)’s systematic review, and DeChurch and Mesmer-Magnus (2010)’s meta-analysis both concluded there was indeed a positive relationship between similarity of mental models and team performance. Also, findings have suggested more similar mental models are linked with higher quality team processes (e.g., Mathieu, et al., 2000). Furthermore, more similar mental models can mediate the relationship between team processes and team performance (e.g., Fisher, Bell, Dierdorff, & Belohlav, 2012), or team processes can mediate the relationship between mental model similarity and team performance (e.g., Santos & Passos, 2013). While a great deal of research on the similarity of mental models within teams exists, only a few studies have focused on engineering design teams (e.g., Lee & Johnson, 2008). To contribute to this literature, this thesis will evaluate the relationship between the similarity of mental models within teams and collaborative success.

While mental model theory suggests groups sharing more similar mental models will be more successful because they are more in sync, there is some debate on what kind of similarity is necessary (e.g., Cannon-Bowers & Salas, 2001). The term similarity can have multiple meanings: two items can be similar because they share identical elements, or they can be similar because they have complimentary elements. Cannon-Bowers and Salas (2001) use the terms overlapping and compatible: overlapping mental models share identical pieces and compatible

mental models share pieces which lead to similar expectations. While researchers do not always clearly define the type of similarity they have measured, the majority of research has investigated within-group mental model overlap. Thus, this thesis will contribute to this conversation by investigating both mental model overlap and compatibility. Overlap will be defined as the degree mental models are identical, and compatibility as the degree of within-group homogeneity.

**Measurement of Similarity.** Researchers have investigated the similarity of mental models within groups by calculating the degree of similarity between teammates via statistical techniques. These techniques have included correlation matrices (e.g., Santos & Passos, 2013), closeness statistics (e.g., Lim & Klein, 2006), multidimensional scaling (e.g., Langan-Fox et al., 2000), distance ratio formulas (e.g., Ross & Allen, 2012), intra-class correlation coefficients (Ayoko & Chua, 2014), or comparing individual team members responses with the average response of the team (Sætrevik & Eid, 2014). The most commonly used technique is a measure of mental model overlap: The closeness statistic (also called *C*) looks at two mental models and quantifies the percentage of identical connections present. Another technique used by collaborative learning researchers to quantify similarity within groups is using group standard deviations as a measure of intragroup agreement (heterogeneity within the group; Cress & Hesse, 2013): This method allows researchers to assess mental model compatibility.

### **Purpose and Research Questions**

The purpose of this study was to examine the centrality of ideas, structure, and similarity of mental models first-year undergraduate engineering students hold about collaboration and engineering design in the context of a course-based engineering design project. The three attributes were exemplified using the following research questions:

**RQ1: What does the centrality of ideas reveal about novice engineers' mental models?**

RQ1a: How does centrality differ across ideas?

RQ1b: Does centrality of ideas differ between performance groups?

**RQ2: What does mental model structure reveal about novice engineers' mental models?**

RQ2a: What patterns in mental model structure are determined through cluster analysis?

RQ2b: Does mental model complexity and differentiation differ between clusters?

RQ2c: Does cluster membership differ between performance groups?

**RQ3: Does within-group mental model similarity relate to group performance grades?**

RQ3a: Does within-group mental model overlap relate to group performance grades?

RQ3b: Does within-group mental model compatibility relate to group performance grades?

**Definitions.** Mental models were represented as Pathfinder networks. Idea units were represented as network nodes. Idea centrality was measured using node degree. Mental model structure was represented by the structure of the corresponding network. Mental model complexity was measured using network centralization, and mental model differentiation was measured using network density. Mental model similarity was measured using within-group network overlap and within-group network compatibility. Overlap was the average proportion of identical network connections within the group. Compatibility was the intragroup agreement on idea centrality.

## Chapter 3: Methods

This chapter outlines the research methods and explains the network analysis techniques used in this thesis.

### Research Design

This exploratory study drew upon descriptive, correlational, and comparative designs. A descriptive design was used to explore the centrality of ideas (RQ1a) and the emergent mental model clusters (RQ2a). A comparative design was used to explore content and structural differences between individual performance levels (RQ1b, RQ2c) and structural differences between emergent mental model clusters (RQ2b). A correlational design was used to explore the relations between network properties (RQ3a/b) and group performance.

### Participants and Sampling Strategy

Participants included a purposeful sample of 251 (57 female) consenting undergraduates enrolled in a first-year engineering course at a midsized university in western Canada. The participation rate was 65%. Mean age was 19.27 years ( $SD = 1.80$ ), and most students identified as first-year students ( $n = 204$ , 81.27%) from the mechanical (33.06%), electrical (18.3%), software (17.83%), civil (17.52%), biomedical (9.56%), and computer (1.59%) engineering programs, or another program (1.99%).

**Individual-level analysis (RQ1 and RQ2).** All 251 students met the following criteria for inclusion in the individual-level analysis: (a) gave consent and (b) had a complete data set.

**Group-level analysis (RQ3).** A subsample of 119 students (33 groups of three; 5 groups of four) met the following criteria for inclusion in the group-level analysis: (a) group had at least 3

and no more than 4 members, (b) all group members consented to participate, and (c) all group members had complete data sets.

### **Research Ethics**

University of Victoria's Human Research Ethics Board (HREB) gave ethical approval for this study, see Appendix C. All students in the course were invited to (a) complete an optional reflection activity for a bonus mark in the course, and (b) consent to participate in research about the reflection activity, see Appendix A. The bonus mark acknowledged the metacognitive value of reflecting on collaboration and engineering design processes (e.g., Chen, Chavez, Ong, & Gunderson, 2017). Students had the option to complete the bonus activity for marks but decline to participate in the research. The bonus mark (1% increase in the final course grade) was administered by course instructors who had access to information about who completed the activity, but no information about student consent to participate in the study.

### **Research Context**

Students worked in self-selected groups over eight weeks to develop the prototype of an autonomous robot using a VEX Robotics Kit. Students were asked to "pretend they [were] working for an engineering firm competing to build this robot" (McGuire et al., 2015, p. 2). According to the instructor, this was a challenging task by design, due in part to a lack of student experience working in teams (McGuire et al. 2015).

### **Procedure**

In the week following the completion of the engineering design project, participants were invited to complete the reflection tool regarding their engineering design knowledge/understanding by (a) one invitation email, (b) one reminder email, and (c) one

laboratory classroom visit. After course grades were submitted, researchers were given access to project grades and GPAs for consenting students.

## Measures

**Task performance.** Task performance measures included: individual level of performance and group performance on three milestones. All grades contributing to task performance measures were graded by two engineering design experts (ENGR120 laboratory supervisors) who followed detailed marking rubrics and came to an agreement on grades (Reid, personal communication, March 22, 2016). The course instructor approved grades.

**Individual level of performance: Low, middle, high performers.** To better understand if mental models played a particularly important role for students who were either high or low achieving, several analyses considered the effect of relative individual performance level.

Students were split into three groups based on their final project grade. Final grades on the engineering design project were computed for each student ( $M = 82.61$ ,  $SD = 10.18$ ) based on (a) group products at three milestones and (b) individual contributions at four milestones<sup>1</sup>.

Categorizing students into performance levels, rather than running analysis on raw final project grades, reduced the power of the analysis but mitigated the risk of an error due to the non-independence of observations introduced by the contribution of group level grades to final project grades.

High performing students were those students who received a grade higher than one standard deviation above the mean ( $n = 30$ ). Low performing students were those students who

---

<sup>1</sup> Final Project Grade = 10% (Individual Milestone 1) + 25% ( /40 Group Milestone 2 + /3 Individual Milestone 2) + 25% ( /53 Group Milestone 3 + 3/ Individual Milestone 3) + 40% ( /110 Group Milestone 4 + /10 Individual Milestone 4)

received a grade lower than one standard deviation below the mean ( $n = 34$ ). All other students were sorted into the middle-performance group ( $n = 187$ ). The distribution of students within groups was as expected: The standard distribution predicts 68% of students within  $\pm 1SD$  from the mean and 74.5% of students were observed within this range, see Figure 3.

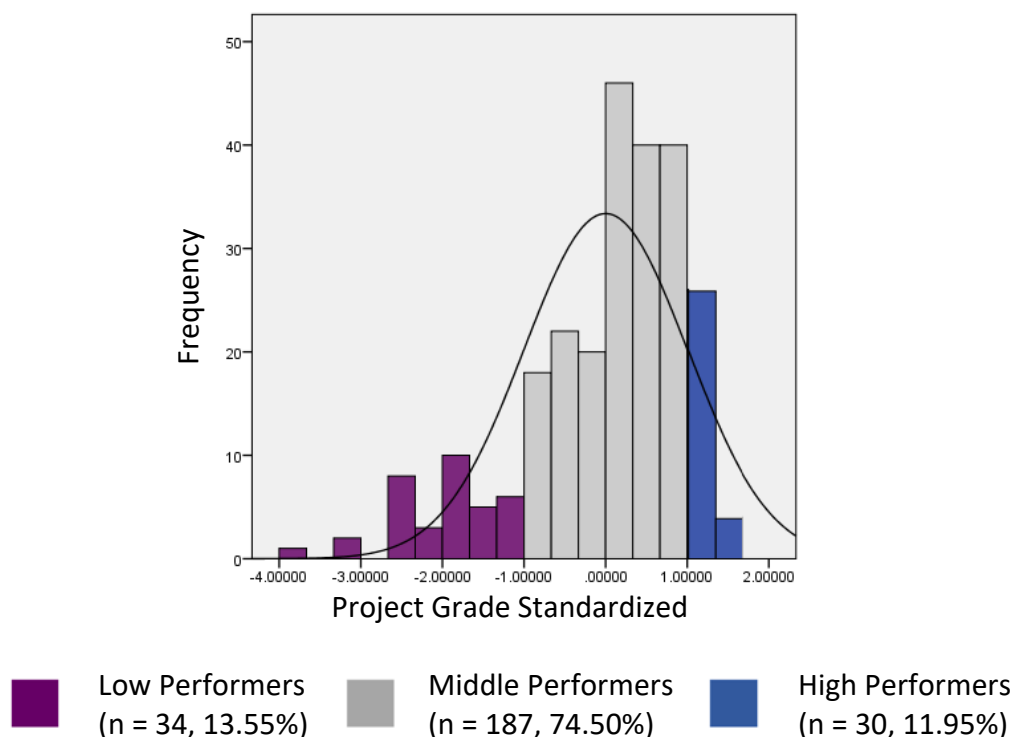


Figure 3. Histogram of the three performance groups.

**Group performance on three milestones.** Group performance measures, used for group-level analysis on mental model similarity, were progress grades on three group milestones. Mean scores for the three group milestones for the full sample, groups included in group-level analysis, and groups excluded from group-level analysis are presented in Table 1. Grades were consistent across the included and excluded groups.

Table 1

*Within-Group Descriptive Statistics for Task Performance Measures (percentages).<sup>2</sup>*

Level	Performance	M (SD)		
		Full Sample of students <i>n</i> = 251	Groups included in group analysis <i>n</i> = 38 (groups)	Groups excluded from group analysis <i>n</i> = 51 (groups)
Group	<b>Milestone 2</b> (Robot motion and source neutralization)	-	89.47 (9.59)	90.13 (6.81)
Group	<b>Milestone 3</b> (Functioning of the robot sensors)	-	80.14 (15.56)	78.61 (13.96)
Group	<b>Milestone 4</b> (Functionality of the completed robot)	-	79.03 (13.56)	78.83 (13.46)
Indiv.	<b>Project Grades</b> (Comprised of milestone grades)	82.61 (10.18)	-	-

**Collaboration mental model instrument.** The collaborative mental model instrument was presented to students as part of the Mental Model Reflection Tool, see Appendix B. This instrument was comprised of seven items, see Table 2, examining aspects of teamwork and collaboration. These items were (a) adapted from past mental model instruments, (b) informed by collaborative theory, and (c) developed in consultation with experts on collaboration. An eighth item, ‘perform effectively as a team’, was initially included in the measure but was later dropped from the analysis because it seemed a general or global item which did not reference a specific collaborative process.

<sup>2</sup> Empty cells are present because (a) Milestones 2 – 4 were scored at the group level and (b) final project grades were scored at the individual level.

Table 2

<i>Collaboration Items.</i>	
<b>Items</b>	<b>Abbreviation</b>
Agree on what the task requires.	Task und.
Negotiate shared goals, roles, and plans.	Planning
Work together to adjust plans as needed.	Adapting
Monitor project progress and team performance.	Monitoring
Foster positive team climate.	Climate
Make full use of each person's knowledge and skills.	Expertise
Fulfill roles and responsibilities.	Roles & resp.

The instrument paired these items in all possible ways to create twenty-one relatedness ranking pairs. Item pairs were presented in a matrix format, see Figure 4. A matrix format was used because (a) it allowed participants to think deeply about pairs of ideas one at a time and return to check answers if needed, (b) pilot testing revealed this method induced less participant fatigue than pairs of items presented one-by-one, and (c) researchers in the field have successfully collected relatedness rankings using matrices (e.g., Bergiel et al., 2015). Also, past research demonstrated systematic presentation of items was more comfortable for participants than randomization of items (Santos, personal communication, March 8, 2016).

	Agree on what the task requires.	Negotiate shared goals, roles, and plans.	Work together to adjust plans as needed.	Monitor project progress and team performance.	Foster positive team climate.	Make full use of each person's knowledge and skills.
Negotiate shared goals, roles, and plans.	---					
Work together to adjust plans as needed.	---	---				
Monitor project progress and team performance.	---	---	---			
Foster positive team climate.	---	---	---	---		
Make full use of each person's knowledge and skills.	---	---	---	---	---	
Fulfill roles and responsibilities.	---	---	---	---	---	---

Figure 4. Collaboration mental model instrument.

Students rated each pair on a 7-point Likert scale from not related (0) to moderately related (3) to highly related (6), see Figure 5. The response scale was consistent with past measures (e.g., Bergiel et al., 2015; Lim & Klein, 2006; Resick, et al., 2010b). A scale of 0 to 6 was adopted for this study because 0 logically represents a null relationship. The scale was anchored at both ends and the midpoint, this method is consistent with Bergiel et al. (2015), and Resick, Dickson, Mitchelson, Allison, and Clark (2010a) and Resick et al. (2010b). Participants were instructed to ‘base your judgments on how you believe the ideas work together to help you successfully design as a team’, see Appendix B.



Figure 5. Scale for relatedness rankings.

**Engineering Design Mental Model Instrument.** Items included seven major steps in the engineering design process, see

Table 3. The resulting measure is widely applicable because it can be applied to many engineering design contexts. Items were created based on a previous instrument piloted by a joint instruction-research project team (Moazzen et al., 2014) to assess engineering design competence. This instrument delineated the major steps in the engineering design process and built from an extensive review of the engineering design literature. The items used in the engineering design mental model instrument were also (a) informed by the engineering design literature (e.g., Davis, Gentili, Trevisan, & Calkins, 2002) and (b) developed in consultation with an engineering design expert.

Table 3

<i>Engineering Design Items.</i>	
<b>Items</b>	<b>Abbreviation</b>
Assess client needs.	Needs
Define problem (criteria, constraints, objectives/goals, requirements).	Problem def.
Identify and assess background information.	Background info.
Generate and evaluate alternative design concepts.	Design concepts
Perform detailed design engineering and analysis.	Analysis
Implement, test and refine detailed design.	Refine
Document detailed design and the supporting analysis.	Document

The seven items were paired in all possible ways to create twenty-one relatedness ranking pairs. The resulting pairs were presented in a matrix format (Figure 6), and participants rated relatedness on a seven-point Likert scale (Figure 5). The matrix format and Likert scale were described in detail under the collaborative instrument.

	Assess client needs.	Define problem (criteria, constraints, objectives/goals, requirements).	Identify and assess background information.	Generate and evaluate alternative design concepts.	Perform detailed design engineering and analysis.	Implement, test and refine detailed design.
Define problem (criteria, constraints, objectives/goals, requirements).	---	*				
Identify and assess background information.	---	*	*			
Generate and evaluate alternative design concepts.	---	*	*	*		
Perform detailed design engineering and analysis.	---	*	*	*	*	
Implement, test and refine detailed design.	---	*	*	*	*	*
Document detailed design and the supporting analysis.	---	*	*	*	*	*

Figure 6. Engineering design mental model instrument.

### Explanation of Network Analysis Techniques and Indices

Before discussing the analysis, it is essential to understand the terms network, node, and edge. *Networks* are “a collection of points joined together in pairs by lines” (Newman, 2010, p. 1). Mental models are often represented as networks. *Nodes* are the points in the network and

represent the ideas in a mental model. *Edges* are the links in the network and represent the connections, or relationships, between ideas in a mental model. Figure 7 provides an example of a network with five nodes and seven edges.

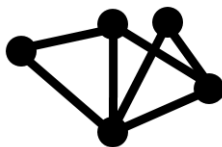


Figure 7. Example of a network with five nodes and seven edges.

This study drew on network analysis techniques to (a) derive networks from responses to the mental model instruments and (b) compute network indices. These network indices were used as variables in the statistical analysis. This section details the network analysis tool used (Pathfinder 7.0), the types of networks derived (pfnets), and the network indices calculated.

**Network Analysis Tool.** Pathfinder (Version 7.0) was used in conjunction with MATLAB (2015b) to create pathfinder networks. Pathfinder is a free data analysis tool developed and maintained by Dr. Roger Schvaneveldt, a Professor Emeritus of Cognitive Science and Engineering at Arizona State University. Pathfinder 7.0 can be found at <http://www.interlinkinc.net/>.

**Network Type.** Pathfinder 7.0 processes proximity data to create networks with the “most efficient connections between [nodes] by considering the indirect connections provided by *paths* through other [nodes]” (Schvaneveldt, 1990, p. ix). These networks are called pathfinder networks or pfnets. To obtain pfnets with the fewest possible links, Pathfinder’s parameters were set as  $r = \infty$  and  $q = n-1$  (where  $n$  equals the number of nodes). The  $q$ -parameter defines the maximum path length within the pfnets and the  $r$ -parameter defines how path distance will be calculated, i.e., Minkowski  $r$ -metric (Schvaneveldt, 1990).

There is a well-established tradition of using pfnets to measure mental models. Mohammed et al. (2000) concluded the degree of support for the reliability of this method is moderate and the degree of support for the validity is acceptable. Furthermore, this method has similar reliability and validity to other methodologies used to represent mental models (e.g., multidimensional scaling).

Figure 8 provides an example of the process for deriving a mental model using Pathfinder. This example is a mental model of 'movie watching'. Proximity data was collected using relatedness rankings, and then the processed proximity data (input file) was feed into Pathfinder 7.0. This program derived a pfnet (output file) from the data.

The nodes in Figure 8 are 'movies', 'happy' and 'friends'. These nodes represent the mental model idea units of 'watching movies', 'being happy' and 'talking to friends'. The pfnet in Figure 8 does not have an edge, or connection, between 'friends' and 'movies' because it was more efficient to link these two nodes through 'happy'. Pfnets do not attach weight or distances to edges. For example, in Figure 8 the edge between 'movies' and 'happy' is identical to the edge between 'happy' and 'friends' even though these edges were rated differently in the reflection tool. Additionally, the pfnets orientation in space is meaningless. It is possible to turn the pfnet in space, and this does not change the meaning of the image.

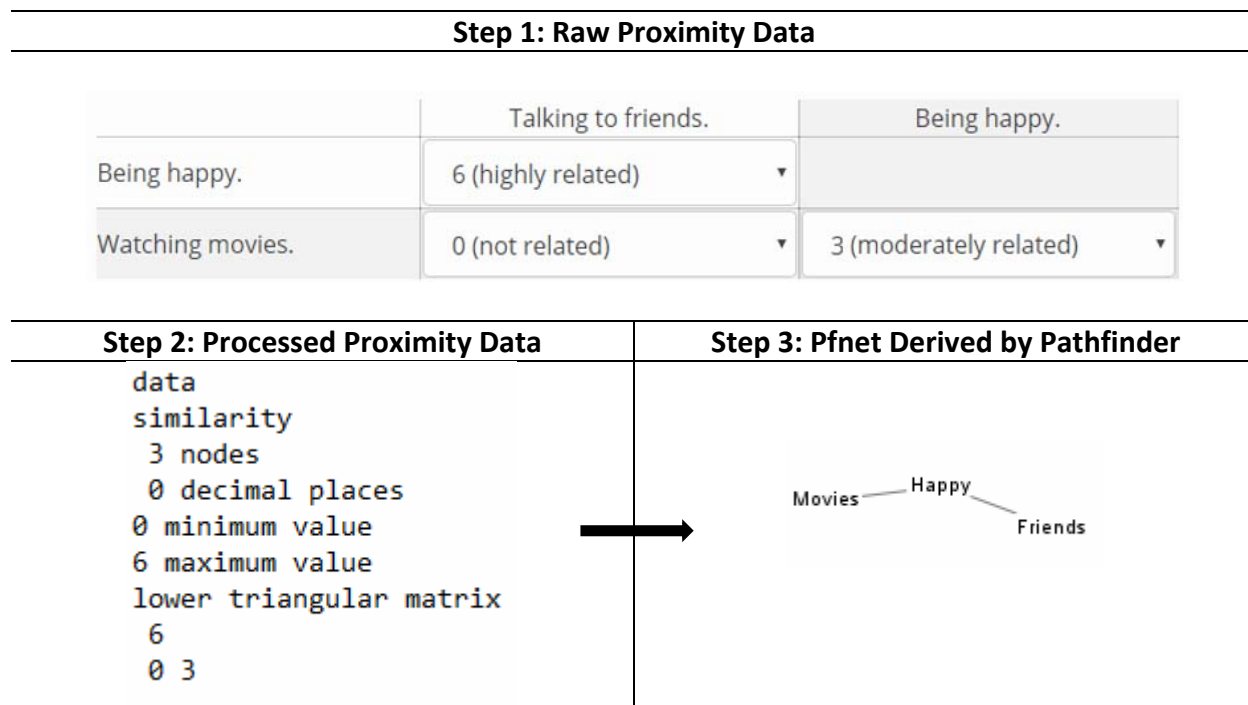


Figure 8. Process used to derive pfnets.

**Network Indices.** Descriptions and analysis drew on four network indices: degree, density, centralization, and similarity. Degree is a node level index. Density and centralization describe the overall structure of a network. Similarity compares networks.

**Degree.** The degree of a node is the number of edges connected to a node (Newman, 2010). In our case, the degree is the number of paths connected to an idea unit. The most central node is the node with the highest degree, and this node is the most salient or powerful node in the network (degree centrality; Newman, 2010; Kadushin, 2012). For this research, the degree of a node measures the centrality of the idea unit.

In our networks, the degree of a node can range from 1 to 6. In Figure 9, Node G has the highest degree in the second and third sample networks, with degrees of four and six respectively. Thus, G is the most salient node in these networks. The first network has five nodes with the highest degree (two), and all the nodes in the fourth network have the same degree. For these networks, none of the nodes stand out as having the most centrality.

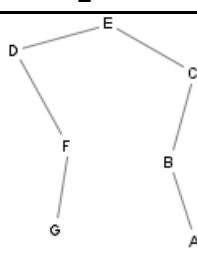
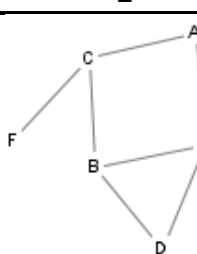
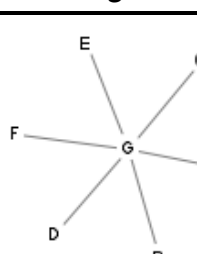
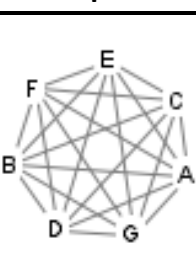
Sample Networks				
	1 <sup>st</sup>	2 <sup>nd</sup>	3 <sup>rd</sup>	4 <sup>th</sup>
				
	<i>linear</i>	<i>hierarchical</i>	<i>star</i>	<i>fully connected</i>
Node	Degree			
A	1	2	1	6
B	2	3	1	6
C	2	3	1	6
D	2	2	1	6
E	2	1	1	6
F	2	1	1	6
G	1	4	6	6
Structural Indices				
Density	0.29	0.43	0.29	1
Centralization	0.07	0.40	1	0

Figure 9. Four sample networks and their corresponding network indices.

**Density.** Density measures network cohesion or differentiation (Kadushin, 2010). Networks with well-connected nodes have high density. In terms of mental models, dense networks represent mental models where idea units are viewed as highly interconnected, and

sparse networks represent the opposite. Dense networks are not as differentiated as sparse networks. For this research, the density of a network measures mental model differentiation.

Density is calculated by dividing the number of existing edges by the number of possible edges within a network (Newman, 2010). Hypothetically, density can range from 0 to 1, with 0 representing a network with no connections and 1 representing a fully connected network.

$$Density = \frac{\text{number of existing links}}{\text{number of possible links}} \quad (1)$$

In our study, density can range from 0.29 to 1; this is because in pfnets all nodes are connected to at least one other node. The first and third networks in Figure 9 have the lowest possible density (density of 0.29), and the fourth network has the highest possible density (density of 1).

**Centralization.** Centralization (Freeman, 1978) measures network structural complexity (Kim & Clariana, 2015) by calculating the “the dispersion in vertex degree” (Anderson, Butts, & Carley, 1999, p. 242). Centralization ranges from 0 to 1, with different levels of centralization representing different structural shapes (Freeman, 1978; Kim & Clariana, 2015). Sample networks with linear, hierarchical, and star shapes are presented in Figure 9. Networks are considered more complex if they have a hierarchical shape (~0.40, Kim & Clariana, 2015).

There are several different ways to calculate centralization (Freeman, 1978). Using the formula chosen by Clariana, Draper, and Land (2011), where  $v$  represented the number of nodes and  $DS$  represented standardized degree:

$$Centralization = (i = 1 \text{ to } v) \Sigma \frac{[\max(DS(v_i)) - DS(v_i)]}{(n - 2)} \quad (2)$$

**Similarity.** Two measures of network similarity were used to compare networks within groups: Overlap and compatibility. For this research, overlap measures the extent mental models are identical and compatibility measures the extent mental models are complimentary.

*Overlap.* Overlap quantifies the number of shared edges in pairs of networks and is a commonly used measure of similarity for pfnets. An edge is considered shared if both networks have the same node-edge-node combination. Pathfinder measures overlap using the *C* statistic. *C* is calculated for pairs of networks and can range from 0 to 1. A score of 0.1 indicates the networks share 10% of their edges, a score of 0.5 indicates 50% shared edges, and a score of 1 indicates the two networks are identical (Lim & Klein, 2006). It is also possible to correct *C* for chance. The Pathfinder *C* statistics yields similar scores to the quadratic assignment proportion (QAP) correlation, an equivalent to Pearson correlations (Lim & Klein, 2006; Mathieu et al., 2005).

In Figure 10 the first comparison, line and star networks, share 9% of their structure or the edge between nodes F and G ( $C = 0.09$ ) and the fifth comparison, line and circle networks, share 86% of their structure or all edges except the edge between A and G ( $C = 0.86$ ).

Comparison Networks		$C$	$C_{corr}$
1 <sup>st</sup>		0.09	-0.09
2 <sup>nd</sup>		0.15	-0.06
3 <sup>rd</sup>		0.29	0.0
4 <sup>th</sup>		0.56	0.35
5 <sup>th</sup>		0.86	0.67

Figure 10. Overlap for five comparison networks.

$C$  is equal to the number of common edges in two networks divided by the total number of edges present in the networks (Schvaneveldt, 1990):

$$C = \frac{(\# \text{ of links in common})}{(\text{total links})}$$

(3)

In small group research, within-group overlap has been measured as the mean overlap of all possible pairs of group members, where  $g$  represents pairs of group members:

$$C_{group} = \frac{(i = 1 \text{ to } g) \Sigma(C(g_i))}{(g)}$$

(4)

It is also possible to calculate overlap corrected for chance. However, this metric is not often used by researchers to evaluate the within-group similarity of mental models.

$$C_{corr} = \frac{(\# \text{ of links in common}) - (\# \text{ of expected links in common})}{(\text{total links})}$$

(5)

Thus, the mean group overlap corrected for chance, where  $g$  represents pairs of group members:

$$C_{group \text{ corr}} = \frac{(i = 1 \text{ to } g) \Sigma(C_{corr}(g_i))}{(g)}$$

(6)

*Compatibility.* Another way to capture within-group similarity is to calculate the intragroup agreement on idea unit centrality (node degree). Intragroup agreement is a measure of heterogeneity of responses within a group and a useful way to aggregate data collected at the individual level to the group level (Cress & Hesse, 2013). Intragroup agreement is the within-group standard deviation: a low score represents high intragroup agreement, and a high score represents poor intragroup agreement. Thus, to measure intragroup agreement on node degree, the within-group standard deviation for each node degree was calculated. A cumulative, or

overall, intragroup agreement can be calculated by adding together the intragroup agreement for each node.

Table 4 presents an example of compatibility calculated using intragroup agreement on node degree. For node one all three individuals had a node degree of one, so the group had had a standard deviation of zero or high intragroup agreement. For node two the individuals had three different node degrees, so the group had a standard deviation of 2.65 or poor intragroup agreement. The cumulative intragroup disagreement is 3.65, or the three node degrees added together.

Table 4

*Example of Compatibility (Intragroup agreement on Node Degree)*

<b>Node Degree</b>	<b>Group Members</b>			<b>Intragroup Agreement (SD)</b>
	<b>Individual 1</b>	<b>Individual 2</b>	<b>Individual 3</b>	
<b>Node 1</b>	1	1	1	0
<b>Node 2</b>	6	1	2	2.65
<b>Node 3</b>	3	2	4	1
<b>Cumulative Intragroup Agreement:</b>				<b>3.65</b>

## **Chapter 4: Results**

This chapter presents the results of the analysis used to address the research questions. Results are presented in two parts: part one describes the analysis for the collaborative mental model and part two describes the analysis for the engineering design mental model. Finally, results are summarized in brief.

### **Data Screening**

Before beginning analysis, data were screened according to the Warner (2013) checklist. Data were proofread against the original source and evaluated for response inconsistencies. Variables were screened for normality, restricted range, and outliers. Variables were approximately normally distributed. Performance measures had negative skew and a small number of outliers. The skew was deemed inconsequential because the sample size was greater than 30 (Howell, 2008). Three methods for treating outliers were considered: winsorizing, eliminating, or leaving as is (Ghosh & Vogt, 2012). All methods can result in statistical bias (Ghosh & Vogt, 2012) and there were few outliers in the data set. As such, outliers were left in the data set. Analysis specific data screening is detailed with the respective analysis.

### **Part 1: Collaboration Results**

This section presents the results of the statistical analysis used to address the research questions for the collaborative mental model. Results are presented separately for each of the research questions.

### What does the centrality of ideas reveal about novice engineers' mental models?

This research question was investigated by examining if collaboration idea centrality differed across ideas and between performance groups. Idea centrality was measured as node degree.

**How does centrality differ across ideas? [RQ1a]** The means and standard deviations for the node degrees, listed in rank order from largest to smallest, are presented in Table 5. The node with the highest mean degree was 'roles and responsibilities' ( $M = 3.38$ ,  $SD = 1.52$ ). This means 'roles and responsibilities' was the most central idea relative to the other ideas. The node with the lowest mean degree was 'monitoring' ( $M = 2.71$ ,  $SD = 1.57$ ). This means 'monitoring' was the least central idea relative to the other ideas.

Table 5

*Means, Standard Dev., and Confidence Intervals for Collaborative Node Degree (N = 251)*

Node	Degree		
	M (SD)	CI 95%	
		Lower	Upper
Roles and responsibilities	3.38 (1.53)	3.19	3.57
Adapting	3.33 (1.53)	3.15	3.52
Planning	3.25 (1.48)	3.07	3.43
Task understanding	3.16 (1.58)	2.97	3.36
Climate	3.14 (1.64)	2.93	3.34
Expertise	3.00 (1.48)	2.81	3.18
Monitoring	2.71 (1.57)	2.52	2.91

A repeated measures analysis of variance (RM-ANOVA), with a Greenhouse-Geisser correction, was conducted to assess whether idea centrality statistically differed across ideas. The following assumptions were tested (a) independence of observations, (b) normality, and (c) sphericity. The assumptions of independence of observations and normality were satisfied.

Mauchly's Test indicated the assumption of sphericity was violated, Mauchly's  $W = 0.88$ ,  $\chi^2(20) = 31.46$ ,  $p < 0.05$ . The epsilon value revealed the violation of the assumption of sphericity was relatively small, Greenhouse-Geisser  $\epsilon = 0.96$ . Because the assumption of sphericity was violated, the Greenhouse-Geisser correction was made when evaluating the significance of the  $F$  test.

Centrality differed across collaboration ideas: results showed the overall  $F$  for differences in mean degree across the seven collaboration nodes was statistically significant:  $F(5.75, 1437.22) = 10.84$ ,  $p < 0.05$ , with a partial  $\eta^2$  of 0.04. Thus, after individual differences were accounted for, about 4% of the variance in degree was related to collaborative node: This is a small effect size. Bonferroni pairwise comparisons revealed 'monitoring' had a statistically lower mean ( $M = 2.71$ ,  $SD = 1.57$ ) than all other nodes, and 'expertise' had a statistically lower mean ( $M = 3.00$ ,  $SD = 1.49$ ) than two other nodes ('adapting' and 'roles and responsibilities'), see Table 6. This means 'monitoring' was the least central idea unit and 'expertise' was less central than some other idea units.

Table 6

*Statistically Significant Mean Differences Between Collaborative Node Degrees (N = 251)*

Comparison	Mean difference	CI 95%	
		Lower	Upper
Monitoring – Roles & resp.	-0.67**	-0.97	-0.37
Monitoring – Adapting	-0.62**	-0.89	-0.35
Monitoring – Planning	-0.53**	-0.83	-0.25
Monitoring – Task understanding	-0.45**	-0.76	-0.14
Monitoring – Climate	-0.42**	-0.71	-0.14
Expertise – Roles & resp.	-0.39**	-0.67	-0.10
Expertise – Adapting	-0.34**	-0.62	-0.06
Monitoring – Expertise	-0.28*	-0.56	-0.00

Note. A Bonferroni correction was applied to all comparisons. \*  $p < 0.05$  \*\*  $p < 0.01$

**Does centrality of ideas differ between performance groups? [RQ1b]** Visual inspection of idea centralities across the three performance groups, see Table 7, suggested performance groups might have different patterns of idea unit centralities. For example, the rank order of centralities differed between the three groups.

Table 7

*Means and Standard Dev. for Collaborative Node Degree by Performance Group (N = 251)*

Node	Degree M(SD)			
	Overall	Low	Middle	High
Roles & resp.	3.38 (1.53)	3.50 (1.75)	3.36 (1.47)	3.40 (1.65)
Adapting	3.33 (1.53)	3.71 (1.80)	3.33 (1.44)	2.97 (1.67)
Planning	3.25 (1.48)	3.79 (1.70)	3.14 (1.43)	3.30 (1.42)
Task und.	3.16 (1.58)	3.65 (1.82)	3.05 (1.51)	3.30 (1.64)
Climate	3.14 (1.64)	3.38 (1.72)	3.08 (1.61)	3.20 (1.79)
Expertise	3.00 (1.48)	3.32 (1.63)	2.95 (1.44)	2.90 (1.61)
Monitoring	2.71 (1.57)	3.35 (1.84)	2.60 (1.51)	2.67 (1.49)

A mixed analysis of variance (mixed-ANOVA) was conducted to assess whether patterns of idea centrality differed statistically across performance levels. Specifically, this analysis looked for an interaction between performance group and idea centrality.

The following assumptions were tested (a) independence of observations, (b) normality, and (c) sphericity, and (d) equality of variances. The assumptions of independence of observations and normality were satisfied. Mauchly's Test indicated the assumption of sphericity was met, Mauchly's  $W = 0.88$ ,  $\chi^2(20) = 31.86$ ,  $p = 0.05$ . Additionally, Box's Test revealed equal covariance matrices, Box's  $M = 52.03$ ,  $F(56, 19776.87) = 0.85$ ,  $p > 0.001$ . Levene's Test indicated equal variance between performance groups for six of the seven node degree variables: the variance of monitoring degree was unequal,  $F(2, 248) = 0.96$ ,  $p < 0.05$ . This was important to keep in mind if post hoc tests were required.

The pattern of idea centrality did not differ between performance groups. The interaction between ideas and performance group was not statistically significant,  $F(12, 1488) = 0.94, p > 0.05$ , see Table 8. Additionally, collaborative idea unit centralities were not statistically lower or higher for any of the performance groups, see Table 8. Results showed there was no statistically significant main effect of performance group,  $F(2, 248) = 2.24, p > 0.05$ , see Table 8.

Table 8

*Results of Mixed-ANOVA Examining Collaborative Centrality Between Performance Groups N = 251)*

	<i>F</i>	<i>df1</i>	<i>df2</i>	<i>p</i>
<b>Performance Group</b>	2.24	2	248	0.11
<b>Ideas x Performance Group</b>	0.94	12	1488	0.51

*Note.* \*  $p < 0.05$  \*\*  $p < 0.01$

### **What does mental model structure reveal about novice engineers' mental models?**

This research question was investigated by identifying structural clusters. Then comparing structural clusters on complexity and differentiation, and performance group composition.

#### **What patterns in mental model structure are determined through cluster analysis?**

**[RQ2a]** A cluster analysis was performed to identify mental model clusters. The analysis used the collaborative node degrees as the seven clustering variables. Following the example of Mathieu et al. (2005), who conducted a cluster analysis based on the same mental model network index (node degree), a hierarchical cluster analysis was performed using Wards' Method as the clustering algorithm.

The sample size ( $n = 251$ ) was appropriate for hierarchical cluster analysis. Formann (1984) recommends a minimum sample size of  $2^k$ , where  $k$  equals the number of variables. For the cluster analysis,  $k$  was seven, and the minimum recommended sample size was 128.

The clustering variables were not standardized because these variables were measured on the same scale (0 to 7) and had similar levels of dispersion (see means and standard deviations in Table 5). The assumptions of (a) lack of multivariate outliers and (b) lack of multicollinearity were met. Multivariate outliers were tested using the Mahalanobis distance method recommended by Tabachnick and Fidell (2001). Multicollinearity was tested by checking that the variance inflation factors (VIF) were less than three and the tolerance levels above 0.10.

Clustering solutions of between one and ten clusters were considered for the final clustering solution. The scree plot revealed the first elbow, or a marked increase in heterogeneity, occurred at two clusters, Figure 11. Additionally, inspection of the dendrogram suggested two was the best clustering solution, see Figure 12. Clustering cross-validation with two random subsamples from the total sample also resulted in two cluster solutions.



Figure 11. Collaboration cluster analysis scree plot.

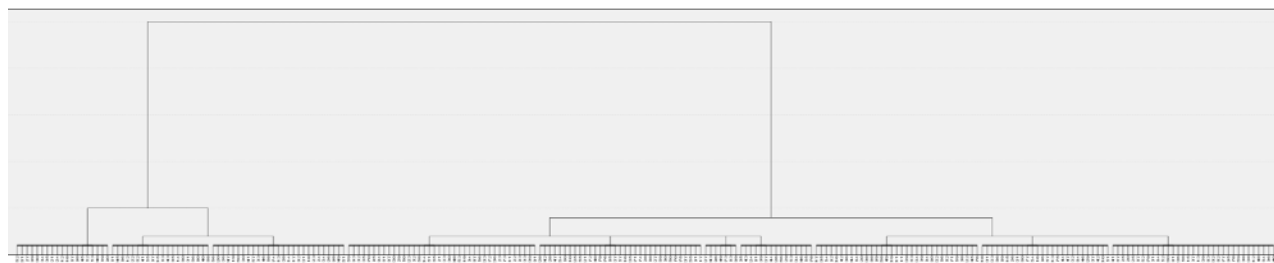


Figure 12. Collaboration cluster analysis dendrogram.

**Cluster Descriptions.** Two mental model clusters emerged based on the centrality of the ideas units within the collaborative mental models. Cluster A was larger ( $n=187$ ) than Cluster B ( $n=64$ ). Descriptive statistics revealed Cluster A had higher project grades ( $M = 83.39$ ,  $SD = 9.35$ ) than Cluster B ( $M = 80.32$ ,  $SD = 12.06$ ), see Table 9. Cluster A was characterized by lower idea centralities and Cluster B by higher idea centralities.

Table 9

*Final Project Grade Descriptive Statistics for Collaborative Clusters*

Task Performance	Cluster M (SD)		
	Overall (N = 251)	A (n = 187)	B (n = 64)
Project Grades	82.61 (10.18)	83.39 (9.35)	80.32 (12.06)

*Cluster A.* Participants in Cluster A had low node degrees, see Table 10. Thus, their mental models had fewer connections between ideas, or were more highly pruned, than the other cluster. Examples of typical Pfnets from the two clusters demonstrating differences in pruning can be found in Table 10. For Cluster A, the node with highest degree was ‘roles and responsibilities’ ( $M = 2.84$ ,  $SD = 1.27$ ), closely followed by ‘planning’ ( $M = 2.82$ ,  $SD = 1.20$ ) and ‘adapting’ ( $M = 2.82$ ,  $SD = 1.25$ ). This means for Cluster A ‘roles and responsibilities’, ‘planning’ and ‘adapting’ were the most central ideas relative to the other ideas. The node with the lowest mean degree was ‘monitoring’ ( $M = 2.05$ ,  $SD = 1.01$ ). This means ‘monitoring’ was the least central idea relative to the other ideas.

Table 10

*Within Cluster Means, Standard Deviations, and Confidence Intervals for Collaborative Node Degrees, and Example Pfnets*

Cluster	Node	Degree			Example Pfnet
		M (SD)	Lower	Upper	
Cluster A (n = 187)	Task und.	2.60 (1.26)	2.42	2.78	
	Planning	2.82 (1.20)	2.65	2.99	
	Adapting	2.82 (1.25)	2.64	3.00	
	Monitoring	2.05 (1.01)	1.90	2.19	
	Climate	2.51 (1.28)	2.32	2.69	
	Expertise	2.48 (1.29)	2.31	2.64	
	Roles & resp.	2.84 (1.27)	2.66	3.03	
Cluster B (n = 64)	Task und.	4.81 (1.21)	4.51	5.11	
	Planning	4.52 (1.49)	4.14	4.89	
	Adapting	4.83 (1.57)	4.52	5.14	
	Monitoring	4.66 (1.26)	4.34	4.97	
	Climate	4.97 (1.13)	4.69	5.25	
	Expertise	4.52 (1.81)	4.18	4.85	
	Roles & resp.	4.95 (1.16)	4.69	5.22	

*Cluster B.* Participants in Cluster B had high node degrees, see Table 10. Thus, their mental models had more connections between ideas, or were less pruned, than the other cluster, see example pfnets in Table 10. For Cluster B, the node with highest degrees was ‘Climate’ (M = 4.66, SD = 1.26), closely followed by ‘roles and responsibilities’ (M = 4.95, SD = 1.16). This means for Cluster A ‘climate’ and ‘roles and responsibilities’ were the most central ideas relative to the other ideas. The nodes with the lowest mean degrees were ‘expertise’ (M = 4.52, SD = 1.81) and ‘planning’ (M = 4.52, SD = 1.49). This means ‘expertise’ and ‘planning’ were the least central ideas relative to the other ideas.

**Does mental model complexity and differentiation differ between clusters? [RQ2b]** A multivariate analysis of variance (MANOVA) was performed to evaluate if there were statistical differences between the two collaborative clusters on a linear combination of two network

structure indices: density and centralization. The assumptions of independence of observations and multivariate normality were met. However, the assumption of homogeneity of covariance was not met, and the assumption of homogeneity of variance for density was not met. Thus, Pillai's Trace was used for the omnibus  $F$  test: Pillai's Trace is robust to violations of homogeneity of variance and co-variance (Warner, 2013).

A statistically significant difference was found, Pillai's Trace = 0.65,  $F(2, 248) = 229.85$ ,  $p < 0.05$ , partial  $\eta^2 = 0.65$ , this effect size indicates a large effect. Follow up analysis, independent samples  $t$ -tests (equal variances not assumed for density), revealed both density and centralization were statistically different between the two clusters. Networks in Cluster A had statistically higher centralization scores ( $M = 0.40$ ,  $SD = 0.18$ ) than Cluster B ( $M = 0.22$ ,  $SD = 0.18$ ),  $t(249) = 6.75$ ,  $p < 0.05$ , Cohen's  $d = 2.75$ . Networks in Cluster A were statistically less dense ( $M = 0.42$ ,  $SD = 0.10$ ) than those in Cluster B ( $M = 0.77$ ,  $SD = 0.15$ ),  $t(80.81) = -17.27$ ,  $p < 0.05$ , Cohen's  $d = 1$ . This means Cluster A had sparser and more complex networks than Cluster B.

Table 11

*Results of MANOVA Examining Relationships Between Collaborative Clusters and Network Indices*

Index	Cluster M(SD)			df	t	d
	Overall (N = 251)	A (n = 187)	B (n = 64)			
Density	0.51 (0.19)	0.42 (0.10)	0.77 (0.15)	80.81	-17.27**	2.75
Centralization	0.36 (0.19)	0.40 (0.18)	0.22 (0.18)	249	6.75**	1

Note. \*  $p < 0.05$  \*\*  $p < 0.01$

**Does cluster membership differ between performance groups? [RQ2c]** To investigate if high, middle, or low performers differed on collaborative cluster membership, a chi-squared statistic was used. Assumptions were met. Table 12 shows the Pearson chi-squared results and indicates performance levels statistically differed on cluster membership ( $\chi^2(2) = 10.00$ ,  $p < 0.05$ ).

There was a small-to-medium effect size,  $\varphi = 0.20$ . This means the proportions of high, middle, and low performing students differed between clusters. Students in the low-performance level were more likely than expected to belong to Cluster B.

Table 12

*Chi-Squared Analysis of Collaborative Cluster Membership Among Performance Level*

Variable	n	Performance Level			$\chi^2$	p
		High	Middle	Low		
<b>Cluster</b>					10.00**	0.00
<b>A</b>	187	22	147	18		
<b>B</b>	64	8	40	16		
<b>Totals</b>	251	30	187	34		

Note. \*  $p < 0.05$  \*\*  $p < 0.01$

### **Does within-group mental model similarity relate to group performance grades?**

This research question looked for associations between group performance measures and two different measures of within-group mental model similarity: overlap and compatibility.

#### **Does within-group mental model overlap relate to group performance grades? [RQ3a]**

To test if there was a statistically significant association between the collaborative mental model overlap shared by individuals within a group and group performance, Pearson correlations were calculated between group overlap measures and grades at group milestones, see Table 13. Pearson correlations were calculated because the assumptions of normality and linearity were met.

There were no statistically significant correlations between group overlap measures and grades at group milestones, see Table 13. This means the within-group overlap on the collaborative mental model was not related to group performance grades.

Table 13

*Pearson Correlations, Means, and Standard Deviations: Collaborative Mental Model Within-Group Overlap and Group Task Performance Measures (n = 38)*

Overlap	Task Performance			M	SD
	Milestone 2	Milestone 3	Milestone 4		
$C_{group}$	-0.05	-0.09	-0.31	0.34	0.11
$C_{group\ corr}$	0.09	0.07	-0.01	0.02	0.05

Note. \*  $p < 0.05$  \*\*  $p < 0.01$

### Does within-group mental model compatibility relate to group performance grades?

**[RQ3b]** To test if there was a statistically significant association between collaborative mental model compatibility and group performance, Pearson correlations were calculated between the cumulative intragroup agreement on node degree and grades at group milestones. Cumulative collaborative compatibility had a Cronbach's  $\alpha$  of 0.75.

Pearson correlations were calculated because the assumptions of normality and linearity were met. Recall, an intragroup agreement of 0 would suggest perfect agreement within the group, and higher numbers would suggest poor agreement within the group: Thus, negative associations would suggest higher agreement and higher performance were related.

Table 14 shows grade at Milestone 2 was moderately correlated with cumulative intragroup agreement,  $r(36) = -0.40, p < 0.05$  and  $r(36) = -0.42, p < 0.05$ . This correlation has a medium effect size: overall  $r^2 = 0.16$ . This means groups with higher cumulative compatibility had higher grades on Milestone 2. Within-group compatibility on the collaborative mental model was related to group performance on Milestone 2.

Table 14

*Correlations, Means, and Standard Deviations for Intragroup Agreement on Collaborative Node Degree and Group Task Performance Measures (n = 38)*

Intragroup agreement on Degree (SD)	Task Performance				
	Milestone 2	Milestone 3	Milestone 4	M	SD
<b>Cumulative</b>	-0.40*	-0.17	-0.18	9.32	2.98

*Note.* \*  $p < 0.05$  \*\*  $p < 0.01$

## Part 2: Engineering design

This section presents the results of the statistical analysis used to address the research questions for the engineering design mental model. Results are presented separately for each of the research questions.

### What does the centrality of ideas reveal about novice engineers' mental models?

This research question examined if engineering design idea centrality differed across ideas and between performance groups. Idea centrality was measured as node degree.

**How does centrality differ across ideas? [RQ1a]** The means and standard deviations for the node degrees, listed in order from largest to smallest, are presented in Table 15. The node with the highest degree was 'problem definition' (M = 3.24, SD = 1.47). This means 'problem definition' was the most central idea relative to the other ideas. The node with the lowest degree was 'background information' (M = 2.88, SD = 1.49). This means 'background information' was the least central idea relative to the other ideas.

Table 15

*Means, Standard Dev., and Confidence Intervals for Engineering Design Node Degree (N = 251)*

Node	M (SD)	Degree	
		CI 95%	
		Lower	Upper
Problem definition	3.24 (1.47)	3.05	3.42
Analysis	3.16 (1.47)	2.97	3.34
Refine	3.06 (1.44)	2.88	3.24
Needs	3.10 (1.49)	2.91	3.29
Design concepts	3.08 (1.52)	2.89	3.27
Background information	2.88 (1.49)	2.70	3.07
Document	2.98 (1.60)	2.78	3.18

An RM-ANOVA was conducted to assess whether idea centrality statistically differed across ideas. The assumptions of independence of observation, normality, and sphericity were satisfied, Mauchly's  $W = 0.91$ ,  $\chi^2(20) = 22.73$ ,  $p = 0.30$ .

Centrality differed across engineering design ideas: results showed the overall  $F$  for differences in mean degree across the seven design nodes was statistically significant:  $F(6, 1500) = 3.27$ ,  $p < 0.05$ , with a partial  $\eta^2$  of 0.01. Thus, after individual differences were accounted for, about 1% of the variance in degree was related to design node. This is a very small effect size. Bonferroni pairwise comparisons revealed the only statistically significant difference in means was between 'problem definition' and 'background information' (mean difference = -0.35, SE = 0.09,  $p < 0.05$ ), see Table 16. For most design idea units, the level of centrality was not statistically different; engineering design ideas generally had the same level of centrality.

Table 16

*Statistically Significant Mean Differences Between Engineering Design Node Degrees (N = 251)*

Comparison	Mean difference	CI 95%	
		Lower	Upper
Problem definition – Background information	-0.35**	-0.63	-0.07

*Note.* A Bonferroni correction was applied to all comparisons. \*  $p < 0.05$  \*\*  $p < 0.01$

**Does centrality of ideas differ between performance groups? [RQ1b]** Visual inspection of idea centralities across the three performance groups, see Table 17, suggested the low-performance group had a different pattern of idea unit centralities than the other two groups. For example, the low group viewed ‘problem definition’ (M = 3.35, SD = 1.63) as a less central idea and the other performance groups viewed ‘problem definition’ as a more central idea.

Table 17

*Means and Standard Dev. for Engineering Design Node Degree (N = 251)*

Node	Degree M(SD)			
	Overall	Low	Middle	High
Problem def.	3.24 (1.47)	3.35 (1.63)	3.25 (1.45)	3.03 (1.47)
Analysis	3.16 (1.47)	3.56 (1.38)	3.09 (1.50)	3.10 (1.37)
Needs	3.10 (1.49)	3.53 (1.64)	3.09 (1.45)	2.70 (1.49)
Design concepts	3.08 (1.52)	3.59 (1.54)	3.06 (1.52)	2.60 (2.40)
Refine	3.06 (1.44)	3.50 (1.62)	2.99 (1.42)	3.03 (1.33)
Document	2.98 (1.60)	3.65 (1.52)	2.88 (1.59)	2.87 (1.57)
Background Info.	2.88 (1.49)	3.12 (2.95)	2.95 (1.44)	2.20 (1.45)

A mixed-ANOVA was conducted to assess whether patterns of idea centrality differed statistically across performance levels. Specifically, this analysis looked for an interaction between performance group and idea centrality.

The following assumptions were tested (a) independence of observations, (b) normality, (c) sphericity, and (d) equality of variances. The assumptions of independence of observations and normality were satisfied. Mauchly’ Test indicated the assumption of sphericity was met, Mauchly’s  $W = 0.92$ ,  $\chi^2 (21.46) = 31.86$ ,  $p > 0.05$ . Additionally, Box’s Test revealed equal covariance matrices, Box’s  $M = 51.90$ ,  $F (56, 19776.87) = 0.85$ ,  $p > 0.001$ . Levene’s Test indicated equal variance between performance groups for all seven node degree variables.

The pattern of idea centrality seemed to differ between performance groups but this difference was not statistically significant. The interaction between ideas and performance group was not statistically significant,  $F(12, 1488) = 1.62, p > 0.05$ , see Table 18.

Table 18

*Results of Mixed-ANOVA Examining Engineering Design Centrality Between Performance Groups*

	<i>F</i>	<i>df1</i>	<i>df2</i>	<i>P</i>
<b>Performance Group</b>	3.09	2	248	0.05
<b>Ideas x Performance Group</b>	1.62	12	1488	0.08

*Note.* \*  $p < 0.05$  \*\*  $p < 0.01$

Visual inspection of engineering design idea unit centralities suggested that low performing students tended to have higher scores than middle or high performing students, see Table 17. However, idea unit centralities were not statistically lower or higher for any of the performance groups. Results showed there was no statistically significant main effect of performance group,  $F(2, 248) = 3.09, p = 0.05$ , see Table 18.

### **What does mental model structure reveal about novice engineers' mental models?**

This research question was investigated by identifying structural clusters. Then comparing structural clusters on complexity and differentiation, and performance group composition.

#### **What patterns in mental model structure are determined through cluster analysis?**

**[RQ2a]** A cluster analysis was performed to identify mental model clusters based on the centrality of engineering design idea units. The analysis used the engineering design node degrees as the seven clustering variables. As in the collaborative cluster analysis, a hierarchical cluster analysis was performed using Wards' Method as the clustering algorithm.

The clustering variables were not standardized because all the clustering variables were measured on the same scale (0 to 7) and had similar levels of dispersion (see means and standard deviations in Table 15). The assumptions of (a) lack of multivariate outliers and (b) lack of multicollinearity were met.

Clustering solutions of between one and ten clusters were considered for the final clusters, see Figure 13. The scree plot revealed the first elbow, or a marked increase in heterogeneity, occurred at three clusters. Additionally, visual inspection of the dendrogram suggested three was an adequate clustering solution (see Figure 14). Clustering cross-validation with two random subsamples from the total sample also resulted in three cluster solutions.



Figure 13. Engineering design cluster analysis scree plot.

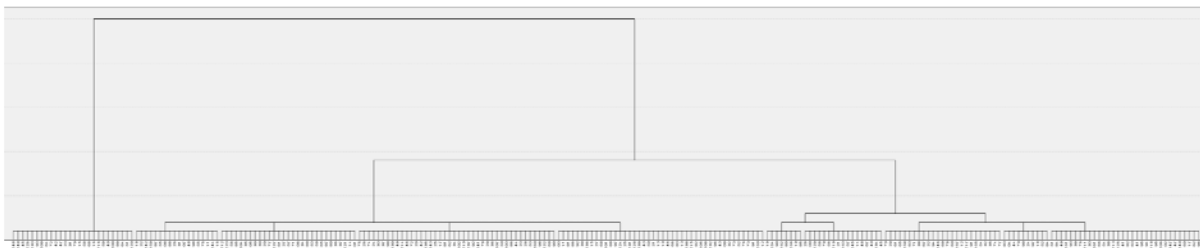


Figure 14. Engineering design cluster analysis dendrogram.

**Cluster Descriptions.** Three mental model clusters emerged. Cluster C was the largest cluster ( $n = 133$ ), followed by Cluster D ( $n = 92$ ) and then Cluster E ( $n = 26$ ). Descriptive statistics revealed Cluster C had higher project grades ( $M = 38.51$ ) than did the other clusters, Table 19. Cluster C was characterized by low idea centralities, Cluster D by middling idea centralities, and Cluster E by high idea centralities.

Table 19

<i>Final Project Grades Descriptive Statistics for Engineering Design Clusters</i>				
Task Performance	Cluster M (SD)			
	Overall (N = 251)	C (n = 133)	D (n = 92)	E (n = 26)
Project Grades	82.61 (10.18)	83.51 (9.49)	81.50 (11.09)	81.92 (10.16)

*Cluster C.* Participants in Cluster C had the lowest node degrees, see **Error! Not a valid bookmark self-reference..** Thus, their mental models had fewer connections between ideas, or were more highly pruned, than the other engineering design clusters. Examples of typical pfnets from the three clusters demonstrating differences in pruning can be found in **Error! Not a valid bookmark self-reference..** For Cluster C, the node with the highest degree was ‘problem definition’ ( $M = 2.38$ ,  $SD = 0.91$ ). This means for Cluster C ‘problem definition’ was the most central idea relative to the other ideas. The node with the lowest mean degree was ‘document’ ( $M = 2.22$ ,  $SD = 1.20$ ), closely followed by ‘client needs’ ( $M = 2.23$ ,  $SD = 0.97$ ) and ‘refine’ ( $M = 2.23$ ,  $SD = 0.91$ ). This means ‘document’, ‘client needs’, and ‘refine’ were the least central ideas relative to the other ideas.

*Cluster D.* Participants in Cluster D had middling node degrees, see **Error! Not a valid bookmark self-reference..** For Cluster C, the node with the highest degree was ‘problem definition’ ( $M = 3.74$ ,  $SD = 1.22$ ). This means for Cluster C ‘problem definition’ was the most central idea relative to the other ideas. The node with the lowest mean degree was ‘background

information' (3.00, SD = 1.33). This means 'background information' was the least central idea relative to the other ideas.

Table 20

*Within Cluster Means, Standard Deviations, and Confidence Intervals for Engineering Design Node Degrees, and Example Pfnets*

Cluster	Node	M (SD)	Degree		Example Pfnet
			Lower	Upper	
			CI 95%		
Cluster C (n = 133)	Needs	2.23 (0.97)	2.07	2.40	
	Problem def.	2.38 (0.91)	2.23	2.54	
	Background info.	2.26 (0.97)	2.09	2.42	
	Design concepts	2.33 (1.13)	2.14	2.52	
	Analysis	2.33 (0.94)	2.17	2.49	
	Refine	2.23 (0.91)	2.08	2.39	
	Document	2.22 (1.20)	2.01	2.43	
Cluster D (n = 92)	Needs	3.60 (1.14)	3.36	3.83	
	Problem def.	3.74 (1.22)	3.49	3.99	
	Background info.	3.00 (1.33)	2.72	3.28	
	Design concepts	3.38 (1.19)	3.14	3.63	
	Analysis	3.58 (1.14)	3.34	3.81	
	Refine	3.52 (1.11)	3.29	3.75	
	Document	3.32 (1.31)	3.04	3.59	
Cluster E (n = 26)	Needs	5.77 (0.51)	5.56	5.98	
	Problem def.	5.81 (0.40)	5.65	5.97	
	Background info.	5.69 (0.55)	5.47	5.91	
	Design concepts	5.85 (0.37)	5.70	5.99	
	Analysis	5.88 (0.43)	5.71	6.06	
	Refine	5.69 (0.55)	5.47	5.91	
	Document	5.69 (0.74)	5.40	5.99	

*Cluster E.* Participants in Cluster E had the highest node degrees, see Cluster C.

Participants in Cluster C had the lowest node degrees, see **Error! Not a valid bookmark self-**

**reference..** Thus, their mental models had fewer connections between ideas, or were more highly pruned, than the other engineering design clusters. Examples of typical pfnets from the three clusters demonstrating differences in pruning can be found in **Error! Not a valid bookmark self-reference..** For Cluster C, the node with the highest degree was ‘problem definition’ (M = 2.38, SD = 0.91). This means for Cluster C ‘problem definition’ was the most central idea relative to the other ideas. The node with the lowest mean degree was ‘document’ (M = 2.22, SD = 1.20), closely followed by ‘client needs’ (M = 2.23, SD = 0.97) and ‘refine’ (M = 2.23, SD = 0.91). This means ‘document’, ‘client needs’, and ‘refine’ were the least central ideas relative to the other ideas.

*Cluster D.* Participants in Cluster D had middling node degrees, see **Error! Not a valid bookmark self-reference..** For Cluster C, the node with the highest degree was ‘problem definition’ (M = 3.74, SD = 1.22). This means for Cluster C ‘problem definition’ was the most central idea relative to the other ideas. The node with the lowest mean degree was ‘background information’ (3.00, SD = 1.33). This means ‘background information’ was the least central idea relative to the other ideas.

**Table 20.** Thus, their mental models had more connections between ideas, or were less pruned, than the other engineering design clusters, see example pfnets in Cluster C. Participants in Cluster C had the lowest node degrees, see **Error! Not a valid bookmark self-reference..** Thus, their mental models had fewer connections between ideas, or were more highly pruned, than the other engineering design clusters. Examples of typical pfnets from the three clusters demonstrating differences in pruning can be found in **Error! Not a valid bookmark self-reference..** For Cluster C, the node with the highest degree was ‘problem definition’ (M = 2.38, SD = 0.91). This means for Cluster C ‘problem definition’ was the most central idea relative to the

other ideas. The node with the lowest mean degree was 'document' ( $M = 2.22$ ,  $SD = 1.20$ ), closely followed by 'client needs' ( $M = 2.23$ ,  $SD = 0.97$ ) and 'refine' ( $M = 2.23$ ,  $SD = 0.91$ ). This means 'document', 'client needs', and 'refine' were the least central ideas relative to the other ideas.

*Cluster D.* Participants in Cluster D had middling node degrees, see **Error! Not a valid bookmark self-reference..** For Cluster C, the node with the highest degree was 'problem definition' ( $M = 3.74$ ,  $SD = 1.22$ ). This means for Cluster C 'problem definition' was the most central idea relative to the other ideas. The node with the lowest mean degree was 'background information' ( $M = 3.00$ ,  $SD = 1.33$ ). This means 'background information' was the least central idea relative to the other ideas.

**Table 20.** For Cluster E, the node with the highest degree was 'analysis' ( $M = 5.88$ ,  $SD = 0.43$ ). This means for Cluster E 'analysis' was the most central idea relative to the other ideas. The nodes with the lowest mean degrees were 'background information' ( $M = 5.69$ ,  $SD = 0.55$ ), 'refine' ( $M = 5.69$ ,  $SD = 0.55$ ), and 'document' ( $M = 5.69$ ,  $SD = 0.74$ ). This means these ideas were the least central ideas relative to the other ideas.

**Does mental model complexity and differentiation differ between clusters? [RQ2b]** A MANOVA was performed to evaluate if there were statistical differences between the three engineering design clusters on a linear combination of two network structure indices: density and centralization. The assumptions of independence of observations and multivariate normality were met. However, the assumptions of homogeneity of co-variance and homogeneity of variance were not. Thus, Pillai's Trace was used for the omnibus  $F$  test; Pillai's Trace is robust to violations of homogeneity of variance and co-variance (Warner, 2013) and Welch's  $F$  test was used to test between-subjects effects because homogeneity of variances was violated.

A statistically significant difference was found, Pillai's Trace = 1.004,  $F(4, 496) = 125.09$ ,  $p < 0.05$ , partial  $\eta^2 = 0.50$ , this indicates a large effect. Follow up analysis revealed both density and centralization were statistically different between the three clusters, respectively: Welch's  $F(2, 69.45) = 1116.71$ ,  $p < 0.05$  and Welch's  $F(2, 92.31) = 125.97$ ,  $p < 0.05$ , see Table 21.

Table 21

*Results of MANOVAs Examining Relationships Between Engineering Design Clusters and Network Indices*

Index	Cluster M(SD)				df 1	df 2	Welch's F	$\eta^2$
	Overall (N = 251)	C (n = 133)	D (n = 92)	E (n = 26)				
Density	0.51 (0.19)	0.38 (0.06)	0.57 (0.08)	0.96 (0.06)	2	69.45	1116.71**	0.97
Centralization	0.32 (0.16)	0.34 (0.16)	0.36 (0.13)	0.05 (0.08)	2	92.32	125.97**	0.73

Note. \*  $p < 0.05$ , \*\*  $p < 0.001$

Games-Howell post hoc tests revealed network density was statistically different between all pairs of clusters: Cluster C (M = 0.38, SD = 0.06), Cluster D (M = 0.57, SD = 0.08), and Cluster E (M = 0.96, SD = 0.05), see Table 22. Additionally, Cluster E (M = 0.05, SD = 0.08) had statistically lower network centralization than Cluster C (M = 0.34, SD = 0.16) and Cluster D (M = 0.36, SD = 0.13), see Table 22. All three engineering design clusters exhibited differing network densities, with Cluster C being the sparsest and Cluster E the densest. Engineering design Cluster C and Cluster D did not differ in their network complexity, but Cluster E had less complex networks.

Table 22

*Games Howell Post Hoc Tests for Engineering Design MANOVA*

	Mean Difference	SE	CI 95%	
			LB	UB
<b>Centralization</b>				
Clusters 1 – 2	-0.02	0.02	-0.07	0.02
Clusters 1 – 3	0.29**	0.02	0.23	0.33
Clusters 2 – 3	0.31**	0.02	0.26	0.36

Density				
Clusters 1 – 2	-0.19**	0.01	-0.22	-0.17
Clusters 1 – 3	-0.58**	0.01	-0.61	-0.55
Clusters 2 – 3	-0.39**	0.01	-0.42	-0.35

Note. \*  $p < 0.05$ , \*\* $p < 0.01$

**Does cluster membership differ between performance groups? [RQ2c]** To investigate if high, middle, or low performers differed on engineering design cluster membership, a Fisher's exact test was used. Fisher's was used rather than Chi-squared because 22% of the cells had expected values of less than five.

Table 23 shows the Fisher's exact test results. Findings indicate performance levels did not statistically differ on engineering design cluster membership,  $\chi^2(1) = 7.84$ ,  $N = 251$ ,  $p > 0.05$ . This means the proportions of high, middle, and low performing students did not differ between clusters.

Table 23

*Chi-Squared Analysis of Engineering Design Cluster Membership Among Performance Level*

Variable	n	Performance Level			$\chi^2$	p
		High	Middle	Low		
Cluster					7.84	0.09
1	133	19	103	11		
2	92	9	64	19		
3	26	2	20	4		
Totals	251	30	187	34		

Note. \*  $p < 0.05$ , \*\* $p < 0.01$

**Does within-group mental model similarity relate to group performance grades?**

This research question looked for associations between group performance measures and two different measures of within-group mental model similarity: overlap and compatibility.

**Does within-group mental model overlap relate to group performance grades? [RQ3a]**

To test if there was a statistically significant association between the engineering design mental

model overlap shared by individuals within a group and group performance, Pearson correlations were calculated between overlap measures and grades at group milestones, see

Table 24. Pearson correlations were calculated because each of the variables were normally distributed and the assumption of linearity was met.

There were no statistically significant correlations between group overlap measures and grades at group milestones, see

Table 24. Results suggest within-group overlap on engineering design mental models was not related to group performance grades.

Table 24

*Pearson Correlations, Means, and Standard Deviations: Engineering Design Mental Model Within-Group Overlap and Group Task Performance Measures (n = 38)*

Overlap	Task Performance			M	SD
	Milestone 2	Milestone 3	Milestone 4		
$C_{group}$	-0.16	-0.03	-0.22	0.36	0.09
$C_{group\ corr}$	0.07	0.14	0.13	0.03	0.06

Note. \*  $p < 0.05$  \*\*  $p < 0.01$

### **Does within-group mental model compatibility relate to group performance grades?**

**[RQ3b]** To test if there was a statistically significant association between engineering design mental model compatibility and group performance, Pearson correlations were calculated between the cumulative intragroup agreement on node degree and grades at group milestones. Cumulative engineering design compatibility had a Cronbach's  $\alpha$  of 0.84.

Pearson correlations were calculated because each of the variables were normally distributed and the assumption of linearity was met. Recall, an intragroup agreement of 0 would

suggest perfect agreement within the group, and higher numbers would suggest poor agreement within the group: Thus, negative associations would suggest higher agreement and higher performance were related. Table 25 shows there were no statistically significant correlations. Within-group compatibility on the engineering design mental model was not related to group performance on any of the three group milestones.

Table 25

*Correlations, Means, and Standard Deviations for Intragroup agreement on Engineering Design Node Degree and Group Task Performance Measures (n = 38)*

Intragroup agreement on Degree (SD)	Task Performance			M	SD
	Milestone 2	Milestone 3	Milestone 4		
<b>Cumulative</b>	-0.15	-0.13	-0.10	9.46	3.37

\*  $p < 0.05$  \*\*  $p < 0.01$

## Chapter 5: Discussion

The purpose of this thesis was to examine (a) the mental models students hold about collaboration and engineering design, and (b) how those mental models relate to individual and group task performance. Separate analyses focused on two types of mental models: collaborative mental models and engineering design mental models. This study extends a very limited body of research on mental models in engineering design contexts by carefully examining the idea units and structure of these mental models, and measuring the engineering design process mental model. This chapter (a) discusses the major findings for each mental model property, (b) summarizes opportunities for future research, and (c) outlines contributions to theory, research, and practice. Major conclusions are summarized at the end.

### **What does the centrality of ideas reveal about novice engineers' mental models? [RQ1]**

Revealing the value or importance students place on various idea provides insight into the salient internal conditions students bring to collaboration. This insight is valuable because central ideas will have an impact on strategic engagement ( Craik, 1952; Hadwin et al., 2017; Rook, 2013). The central ideas within the collaboration and engineering design mental models were investigated by asking two questions: How does centrality differ across ideas? Does centrality of ideas differ between performance groups? Three main themes emerged: (a) monitoring was viewed as the least central collaborative idea, (b) students placed equal importance on the engineering design ideas, and (c) patterns did not differ statistically between performance levels.

**Monitoring was viewed as the least central collaborative idea.** Students viewed the monitoring idea unit as being less central than other collaborative idea units. There are several possible explanations for this finding. It might suggest students placed less importance on

monitoring. Alternatively, students might not understand how monitoring relates to other collaborative processes. The undervaluing of monitoring is in line with prior research demonstrating students often fail to monitor or inadequately monitor their own learning (Butler & Winne, 1995; Kuhn, 2000; Lan, 2005; Winne 2011).

However, theory suggests all idea units included in the collaborative measure are key components of socially-shared regulation of learning (SSRL), and the interplay between these components leads to success (e.g., Hadwin et al., 2017; Salas, Sims, & Burk, 2005). Theoretically, Hadwin et al. (2017) emphasized metacognitive monitoring as a critical component of successful SSRL because effective collaborative planning, enacting, and adapting are dependent on monitoring and evaluating. Furthermore, Lan (1996) found a positive association between monitoring and performance for university students (studying statistics).

The low centrality of monitoring might be explained by a miscalibration between the actual importance of monitoring and the perceived importance of monitoring; Students may under-value the importance of monitoring to collaborative success. Alternatively, students may view monitoring as less central than other processes because they do not recognize instances where they have monitored (e.g., they are not meta-cognitively aware of monitoring). As Winne (2017) points out, “is often challenging for students (and other thinkers) to thoroughly and reliably observe their cognitive operations” (p. 38).

**Students placed equal importance on the engineering design ideas.** None of the engineering design idea units were overwhelmingly more or less central. A review of the literature revealed no research investigating the centrality of ideas within engineering design mental models. However, theory suggests each of the idea units should be equally salient. The

engineering design process is iterative and loosely sequential, and each step depends on information created during other steps (Dym et al., 2005). As such, each step is valuable and the process should not be consumed or preoccupied with one step.

The equal centralities of engineering design ideas might be explained by the fact students were enrolled in a course where they learned the inherent value of each step in the engineering design process. The equality of ideas suggests the approach taken by educators to impart the importance of the various engineering design stages was successful. Future research should investigate idea unit salience in expert mental models of engineering design. First, it is critical to investigate if experts' mental models hold true to the theoretic models used by engineering educators. Second, it would be interesting to compare expert and novice mental models of engineering design on idea unit centrality.

**Patterns did not differ statistically between performance levels.** Idea centrality was not lower or higher for low, middle, and high-performance groups. Additionally, while visual inspection suggested the low, middle, and high-performance groups might show different patterns of idea centrality, particularly for the engineering design mental model, there was no statistical difference between performance groups for either mental model. This finding was surprising, high-performance students are expected to hold more useful mental models, or mental models with different characteristics, than low-performance students. Research has suggested novices and experts hold different quality mental models characterized by different properties (e.g., Glaser, 1985). It is possible that high and low performing students do not differ on idea centrality but do differ on another mental model property.

**What does mental model structure reveal about novice engineers' mental models? [RQ2]**

Investigating emergent structural clusters is important because it can reveal the quality or expertise of a mental model (e.g., Mathieu, et al., 2005). Structure was investigated with three questions: What patterns in mental model structure are determined through cluster analysis? Does mental model complexity and differentiation differ between clusters? And, does cluster membership differ between performance groups? These questions were investigated by identifying the distinct clusters that emerged during a cluster analysis based on idea centrality, testing if measures of complexity and differentiation were statistically different between clusters, and by comparing clusters to determine if their composition of high, middle, or low performers differed.

Findings suggested clusters formed based on the level of connection pruning: Networks with fewer edges clustered together, while networks with more edges clustered together. Analysis comparing clusters revealed (a) level of mental model pruning is an indicator of mental model quality or expertise, and (b) quality of collaborative mental models, but not design mental models, was associated with performance.

***Level of pruning is an indicator of mental model quality or expertise.*** Findings suggested more highly pruned clusters were more complex and differentiated than less pruned clusters. Taken together, these findings might suggest the level of pruning is an indicator of mental model quality or expertise. Essentially, pruning unnecessary connections is useful, and higher levels of pruning might be analogues to higher levels of expertise.

Level of pruning as an indicator of expertise is supported by theory on expertise suggesting, within their own domains, expertise perceive meaningful patterns and represent

problems at a deep level (Glaser & Chi, 1988). In this case, findings may suggest students in the highly pruned clusters recognize patterns of salient connections akin to the way experts would recognize such patterns. This conclusion is supported by Mathieu et al. (2005)'s demonstration that the most experienced teamwork researchers had teamwork mental models with highly pruned connections (on average team attributes were moderately related and half of all possible links had been pruned).

The connection of pruning and expertise is also supported by research demonstrating experts have complex, function, and highly organized knowledge as compared with novices (Chi, Glaser, Rees, 1982; Glaser, 1985; Hambrick & Hoffman, 2016). Students who have pruned their mental model connections have more complex and differentiated networks organized in a way unpruned mental models are not, Figure 15 provides an example of this phenomenon.

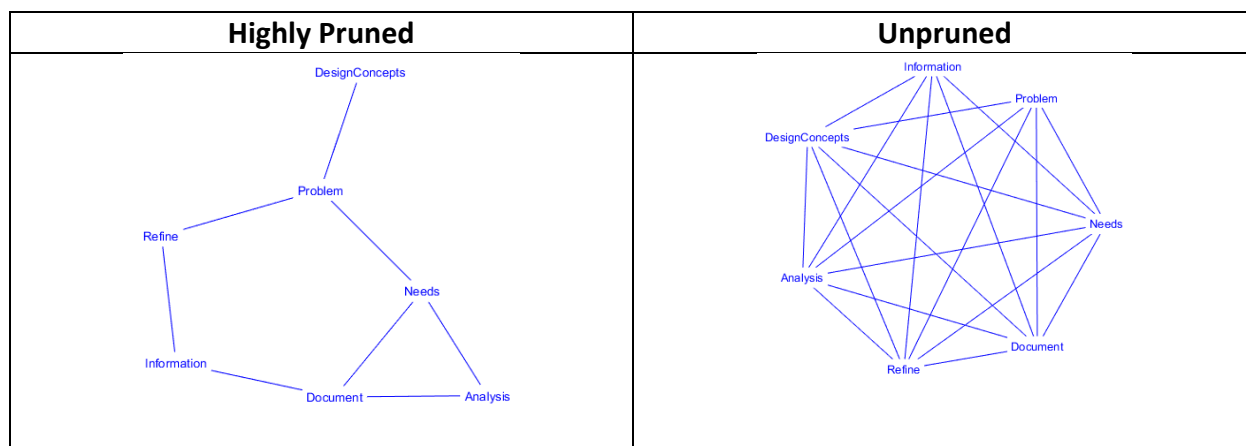


Figure 15. Examples of a highly pruned mental model and an unpruned mental model.

**Quality of collaborative mental models was associated with performance.** Findings for the collaborative mental model suggested students in the low-performance group were more likely than expected to belong to the unpruned, lower quality, cluster. This finding had a small-

to-moderate effect size. Additionally, students in the unpruned collaborative cluster tended to have slightly lower project grades than students in the other collaborative cluster. These findings were not observed for the design mental model.

It is not surprising that more students in the low-performance group had unpruned collaborative mental models. As discussed, evidence from this study suggests unpruned mental models are of lower quality or expertise than highly pruned mental models. Furthermore, theory suggests mental model quality or expertise should be associated with effectiveness of cognition and performance (e.g., Glaser, 1987). However, it is surprising this was true for the collaborative mental model and not the engineering design mental model. Engineering education theory suggest both elements, engineering design and collaboration, are critical to successful collaborative engineering design (e.g., Davis et al., 2002; Dym et al., 2005).

There is a dearth of research comparing the usefulness of collaborative mental model and engineering design mental model quality in predicting performance. In other domains, there have been some investigations of the relationship between quality of teamwork and task work mental models in predicting performance (at the group level). This body of research has generally assessed the quality of mental models by comparing them to mental models derived from experts. In agreement with the findings of the current study, Lim & Klein (2006) found the accuracy of teamwork mental models was more predictive of team performance than the accuracy of task work mental models.

The connection of performance and quality of collaborative mental models, but not engineering design mental models, might be explained by collaborative mental model quality acting as a gatekeeper during the engineering design process: If group members do not have

useful understandings of how to collaborate, the quality of their engineering design mental models may become inconsequential. Future research should investigate if quality, or expertise, of collaborative mental models and design mental models interact to predict performance.

Alternatively, this finding might also be explained by the course context obscuring a possible association between quality of engineering design mental models and performance. Students were enrolled in a course where they were explicitly taught about the engineering design process and students may have misrepresented their actual engineering design mental models to better fit what they had been taught.

### **Does within-group mental model similarity relate to group performance grades? [RQ3]**

Examining the importance of similarity within teams is important because within-group mental model similarity is thought to afford the group's coordination of action (Cannon-Bowers et al., 1993) and development of shared understanding is critical to successful collaboration (Roschelle & Teasley, 1995). However, there has been some debate as to (a) whether mental models should be overlapping or compatible (Cannon-Bowers & Salas, 2001; Cooke, Salas, Cannon-Bowers, and Stout, 2000), and (b) what types of mental models should be shared during collaborative engineering design (Badke-Schaub et al., 2007b). The importance of similarity of mental models within groups was investigated by examining if mental model overlap [RQ3a] or mental model compatibility [RQ3] were related with task performance. Findings suggest mental model compatibility was related to performance, but mental model overlap was not. This finding was true for the collaborative mental model at the first group performance grade, but not for the engineering design mental model.

**Compatibility is more important than overlap.** Degree of overlap was not related to task performance, but the degree of compatibility of the collaborative mental model was related to task performance at the first group milestone (Milestone 2). During collaborative engineering design, it might be more important for students to share compatible mental models rather than overlapping or identical mental models.

Mental model theory would suggest mental models do not need to be overlapping or identical to enhance performance. Theory states similar mental models are useful because they afford groups to be in sync or on the same page (Cannon-Bowers et al., 1993). Compatible mental models allow for this synchronicity: group members can understand each other or work in concert without having overlapping or identical understandings (Cannon-Bowers & Salas, 2001).

Research on mental model similarity has focused on mental model overlap rather than mental model compatibility. In contrast to the current finding, there is a plethora of research suggesting mental model overlap is predictive of team performance (DeChurch & Mesmer-Magnus, 2010; Mohammed et al., 2010). Compatibility might be more important than overlap during collaborative engineering design because in this situation some cognitive diversity might be useful (e.g., Milliken et al., 2003).

**Students who are successful at the beginning of collaboration develop more compatible collaborative mental models.** Collaborative mental model compatibility was moderately related with performance at the first group milestone (Milestone 2) and not statistically related to performance at any of the other milestones. Furthermore, engineering design mental model compatibility was not related to performance at any group milestone. This suggests groups that

developed more compatible collaborative mental models by the end of the project performed better at the beginning of the project.

It is not surprising compatibility of collaborative mental models is positively related to collaborative performance. However, it does seem surprising engineering design mental models were not related to performance. For both mental model types, theory would suggest better shared mental models support collaborative success (Cannon-Bowers et al., 1993; Salas et al. 2005). However, specifically in relation to engineering design, Badke-Schaub et al. (2007b) posit “more sharedness is not always better” because cognitive diversity might “broaden the solution space” but suggest at least a shared mental model of teamwork is essential to successful collaborative engineering design (p. 11).

Little research exists on the relationship between mental model similarity and performance for collaborative engineering design teams. In one exception, Bierhals et al. (2007) found mental model similarity for teamwork and general team processes was related to performance during collaborative engineering design. However, Bierhals et al. did not specifically consider mental model of the engineering design process.

### **Opportunities for Future Research**

While the current study provides a valuable window into the mental models of first-year engineering students, the study is not without limitations and opportunities for future research.

**Multiple levels of analysis.** Small group research is challenging because of the multiple levels of analysis (Janssen, Cress, Erkens, & Kirschner, 2013). This study relied on data collected at the individual level and data collected at the group level. To avoid violating the assumptions of statistical tests, e.g., independence of observations, individual data were aggregated to the

group level (as was done for similarity analysis) or reduced into categories (as was done for individual performance). Aggregation moved the level of analysis from the individual to the group. Reduction into performance categories reduced the influence of group level grades on the individual performance measure, i.e., reduced the influence of observation non-independence. Future research could find way to independently measure individual design performance.

**Authentic learning situations.** Little research has investigated mental models of collaboration and engineering design in authentic learning situations. The use of an authentic learning situation for data collection was a strength of the study. However, researchers did not have control over the design of the group project or input into how the project was marked. This is a limitation because it was not possible, for example, for researchers to ensure standardization of grading practices. Research in authentic learning situations should continue, and researchers must continue find ways to effectively collaborate with instructors in course-based research.

**Experimental investigations.** This study does provide a valuable description of mental models, and the associations between mental models and performance. While this may be the case, this study cannot make any causal inferences. This design of the study was not experimental, and the statistical tests could not evaluate causality. The findings could direct future experimental studies.

**Mental models over time.** Mental model theory and research suggest mental models are dynamic and unstable (Al-Diban, 2012; Darabi et al., 2010; Derry, 1996; Seel, 2001). In this study the reflection tool was administered at one timepoint at the end of the project. By measuring mental models at only one timepoint, the study lacks a rich description of how mental models

change over time and events. Future research should sample mental models throughout the process of collaborative engineering design.

Additionally, this study looked for relationships between mental models measured at the end of the project and performance throughout the project, but the students' mental models likely changed throughout the project. To try to mitigate this flaw, the reflection tool asked students to reflect on their most recent project while completing the tool. Thus, the reflection tool aimed to elicit mental models representing the students' overall experience in the project. In research with a time component, it would be valuable to sample mental models and performance in tandem at all timepoints.

**Free recall of mental models.** The process of administering the reflection tool might have changed students' mental models. For example, the tool provided idea units to students rather than eliciting idea units freely. Thus, the tool might have introduced new ideas into students' mental models. This is a known concern in mental model research (Mohammed et al., 2010). The study attempted to reduce the risk of this occurring by carefully selecting ideas to include in the measures. Future research could build on the findings of this study but allow for free recall of mental models using a different collection technique, for example: concept mapping.

**Reliability and validity testing.** The mental model instruments used in this study have not undergone rigorous reliability and validity testing. While this is a concern, the methodology used in the measures is commonly used to measure mental models, and the method's validity and reliability have been evaluated by other researchers (e.g., Mohammed et al., 2000). Additionally, the items used in this study were approved by experts, suggesting content validity, and appeared

to measure what they purported to measure, suggesting face validity. A next step will be to further evaluate the measures' reliability and validity.

**Mental models throughout post-secondary.** This study focused on a non-probability sample of first-year engineering students in a specific course. The findings can be used in this local course context to inform educational practice; however, the findings may not generalize to other undergraduate populations. Future research should build on findings from this sample of first-year students and sample students across their undergraduate careers.

**Trace data.** While it is vital to understand how students think about collaboration and design, it is also critical to investigate how those thoughts translate into action. This study did not capture trace data on student's collaborative processes, but rather focused on self-reported mental models. Trace data collected during learning are at times "poorly calibrated" with self-reports of learning (Hadwin, Nesbit, Jamieson-Noel, Code & Winne, 2007). Thus, it would be valuable to investigate how mental models translate into action using trace data.

### **Implications for theory, research, and practice**

**Implications for theory.** This thesis contributes to theory in three major ways. First, findings point to the importance of mental model compatibility but not mental model overlap. Mental model theory suggests teams sharing more similar mental models will be more successful because they are more in sync (Cannon-Bowers et al., 1993). However, the term similarity can have multiple meanings: two items can be similar by sharing identical elements, or they can be similar because they have complimentary elements. The findings of this study suggest compatibility, or complementary elements, might be more valuable than overlap, or identical elements. Mental model theory and research should clarify what are critical forms of similarity.

Second, findings suggest students with more highly pruned mental models had more expert mental models, characterized by higher levels of complexity and differentiation. Additionally, low-performance students were more likely than expected to exhibit lower levels of collaborative mental model pruning. Theory on the nature of expertise describes expert memory structures as capturing meaningful patterns on a deep level (Glaser & Chi, 1988). This thesis contributes to theory by describing expert mental models as having dropped unessential connections, e.g., highly pruned.

Third, findings suggest collaborative mental models are more related to success than engineering design mental models. Students regulate both their task work and their collaboration. Students' mental models of collaboration are the standard to which they regulate their individual and group contributions to collaboration. The way students understand collaboration, their collaboration standard, is linked with success. However, the way students understand engineering design, their engineering design standard or engineering design mental model, was not statistically linked with success. This contributes to regulation theory by suggesting that understandings of collaboration are particularly important to the collaborative success of novices.

**Implications for research.** This thesis contributes to research in three major ways. First, findings provide insight into the collaboration and engineering design mental models of novice engineers during an authentic learning situation. There has been little research on mental models of engineering design, especially for authentic engineering design tasks. The students involved in the current study were novices, and their understanding of engineering design was informed by theoretical models of engineering design and teamwork taught in their coursework. Future

research could investigate the differences and similarities between the mental models of novice engineers and those of more experienced or professional design engineers. Examining expert mental models would be useful because the purpose of the group engineering design projects is to develop engineering design expertise.

Second, this study suggested collaborative mental models and engineering design mental models differ in how they contribute to success during collaborative engineering design. Specifically, this thesis found there were two instances where collaborative mental models were associated with performance while there were no instances for the engineering design mental model. However, collaborative mental models and engineering design mental models might interact to contribute to success. Further research should investigate how the collaborative and engineering design mental models work together.

Third, this study closely investigated the idea units and structure of collaboration and engineering design mental models. Little research has investigated mental models at this granularity. Instead, research has focused on similarity of mental models between collaborators. By investigating at this level of granularity, it became clear students view monitoring as the least central collaborative idea, and higher levels of mental model pruning are more adaptive. These findings create opportunities for research to focus in on mental models at a finer grain. For example, research could investigate if the perceived value, or salience, of monitoring is related to the frequency monitoring actually occurs, or if particular forms of pruning are more useful.

**Implications for practice.** The findings of this thesis can be used to inform future educational practice. Implications can be delineated in four broad themes: collaborative mental models are critical to successful engineering design, development of compatible collaborative

mental models throughout a project may contribute to early group success, mental model pruning should be encouraged, and students underemphasize the value of monitoring.

*Collaborative mental models are critical to successful engineering design.* Compatibility of collaborative mental models was more related to performance than the compatibility of engineering design mental models. Additionally, low performers were more likely to belong to a particular collaborative cluster but were equally distributed among design clusters. How students think about collaboration is just as important to success, as how students think about engineering design. Engineering educators must recognize well developed mental models of collaboration are critical to engineering design success and build the development of collaborative expertise into engineering programs in systematic ways. Students should be taught to collaborate, just as they are taught to design. It would be useful for students to have opportunities to both learn about and practice collaborative processes before participating in high-stakes collaborative engineering design projects.

*Development of compatible collaborative mental models throughout a project may contribute to early group success.* Groups who developed more compatible mental models by the end of the project were more successful at the beginning of the group project. Engineering educators should create opportunities for groups to develop compatible mental models of collaboration and encourage groups to plan for teamwork in addition to planning task work.

*Mental model pruning should be encouraged.* As early as their first-year, students begin to eliminate unnecessary connections within their mental models and develop complex understandings of collaboration and engineering design. Engineering educators should

encourage the pruning process. By identifying students who have not pruned their mental models early in the semester, it might be possible to intervene and support the pruning process.

*Students underemphasize the value of monitoring.* Students viewed monitoring as the least central collaborative idea unit. However, monitoring and evaluating are critical aspects of regulating learning. Engineering educators should highlight the role of monitoring/evaluating progress and performance in successful engineering design. Monitoring could be scaffolded through scripts or visualizations: Winne (2017) suggests metacognitive monitoring can be encouraged through learning analytics (visualizations) and recommendations (scripts).

## **Conclusions**

This thesis aimed to contribute to a more extensive research project aimed at examining undergraduate engineering student's understandings of engineering design and teamwork and fill a gap in the literature on mental model of collaborative engineering design. To meet this aim, this thesis drew on theory and research from the learning sciences to investigate the mental models of engineering design and collaboration that first-year students formed during an eight-week long engineering design project. Results suggest within-group collaborative mental model compatibility is associated with group performance and low performing students are more likely than expected to hold low quality collaborative mental models. However, engineering design mental models were not associated with performance. Furthermore, high-quality mental models are characterized by higher levels of connection pruning. From these findings, we might conclude collaborative mental models are an essential factor to consider when preparing undergraduate engineering students to engage in collaborative engineering design.

## References

- Accreditation Board for Engineering and Technology [ABET] (2016). *Criteria for accrediting engineering programs 2016 -2017*. Retrieved from <http://www.abet.org/accreditation/accreditation-criteria/criteria-for-accrediting-engineering-programs-2016-2017/#objectives>
- Al-Diban, S. (2012). Mental models. In N. M. Seel (Ed.) *Encyclopedia of the sciences of learning* (p. 2200- 2204). New York, NY: Springer.
- Al-Diban, S., & Ifenthaler, D. (2011). Comparison of two analysis approaches for measuring externalized mental models. *Journal of Educational Technology & Society*, 14(2), 16-30. Retrieved from <http://www.jstor.org/stable/jeductechsoci.14.2.16>
- Anderson, B. S., Butts, C., & Carley, K. (1999). The interaction of size and density with graph-level indices. *Social networks*, 21(3), 239-267. DOI: 10.1016/S0378-8733(99)00011-8
- Ayoko, O. B., & Chua, E. L. (2014). The importance of transformational leadership behaviors in team mental model similarity, team efficacy, and intra-team conflict. *Group & Organization Management*, 39(5), 504-531. DOI: 10.1177/1059601114550080
- Badke-Schaub, P., Lauche, K., & Neumann, A. (2007a). Team mental models in design. *CoDesign*, 3, 1-4. DOI: 10.1080/15710880601170743
- Badke-Schaub, P., Neumann, A., Lauche, K., & Mohammed, S. (2007b). Mental models in design teams: a valid approach to performance in design collaboration?. *CoDesign*, 3(1), 5-20. DOI: 10.1080/15710880601170768

- Bakhtiar, A. (2015). *Challenges in collaborative learning: where do we go from here?*  
Unpublished manuscript, Department of Educational Psychology, University of Victoria,  
Victoria, BC, Canada.
- Barron, B. (2003). When smart groups fail. *The Journal of the Learning Sciences*, 12(3), 307-359. DOI: 10.1207/S15327809JLS1203\_1
- Bergiel, E. B., Gainey, T. W., & Bergiel, B. J. (2015). Understanding the relationship between mental models, conflict and conflict asymmetry. *Team Performance Management*, 21(7/8), 320-338. DOI: 10.1108/TPM-02-2015-0009
- Bierhals, R., Schuster, I., Kohler, P., & Badke-Schaub, P. (2007). Shared mental models—linking team cognition and performance. *CoDesign*, 3(1), 75-94. DOI: 10.1080/15710880601170891
- Boekaerts, M. & Niemivirta, M. (2000). Self-regulated learning: Finding a balance between learning goals and ego-protective goals. In M. Boekaerts, P.R. Pintrich & M. Zeidner (Eds.), *Handbook of Self-regulation* (pp. 417 - 450). San Diego, CA: Academic Press.
- Borrego, M., Karlin, J., McNair, L. D., & Beddoes, K. (2013). Team effectiveness theory from industrial and organizational psychology applied to engineering student project teams: A research review. *Journal of Engineering Education*, 102(4), 472-512. DOI: 10.1002/jee.20023
- Bucciarelli, L. L. (1994). *Designing engineers*. Cambridge, MA: MIT press.
- Burtscher, M. J., Kolbe, M., Wacker, J., & Manser, T. (2011). Interactions of team mental models and monitoring behaviors predict team performance in simulated anesthesia

- inductions. *Journal of Experimental Psychology: Applied*, 17(3), 257. Retrieved from <http://psycnet.apa.org/buy/2011-21481-006>
- Butler, D. L., & Winne, P. H. (1995). Feedback and self-regulated learning: A theoretical synthesis. *Review of educational research*, 65(3), 245-281.
- Canadian Engineering Accreditation Board [CEAB] (2015). *2015 accreditation criteria and procedures*. Ottawa, ON: Engineers Canada. Retrieved from [https://www.engineerscanada.ca/sites/default/files/accreditation\\_criteria\\_procedures\\_2015\\_0.pdf](https://www.engineerscanada.ca/sites/default/files/accreditation_criteria_procedures_2015_0.pdf)
- Cannon-Bowers, J. A., & Salas, E. (2001). Reflections on shared cognition. *Journal of organizational behavior*, 22(2), 195-202. DOI: 10.1002/job.82
- Cannon-Bowers, J.A. Salas, E. & Converse, S. (1993). Shared mental models in expert team decision making. In N.J. Castellan (Ed.), *Individual and group decision making* (pp. 221 - 246). Hillsdale, NJ: Lawrence Erlbaum.
- Carley, K. M. (1997). Extracting team mental models through textual analysis. *Journal of Organizational Behavior*, 18, 533–558. Retrieved from <http://www.jstor.org/stable/3100264>
- Carley, K., & Palmquist, M. (1992). Extracting, representing, and analyzing mental models. *Social forces*, 70, 601-636. DOI: 10.1093/sf/70.3.601
- Casner-Lotto, J. (2006). *Are they ready to work? Employer's perspectives on the basic knowledge and applied skills of new entrants to the 21<sup>st</sup> century U.S. workforce*. USA: The Conference Board, Partnership for 21<sup>st</sup> Century Skills, Corporate Voices for Working Families, and Society for Human Resource Management. Retrieved from Partnership for

21<sup>st</sup> Century Learning website

[http://www.p21.org/storage/documents/FINAL\\_REPORT\\_PDF09-29-06.pdf](http://www.p21.org/storage/documents/FINAL_REPORT_PDF09-29-06.pdf)

Chen, P., Chavez, O., Ong, D. C., & Gunderson, B. (2017). Strategic Resource Use for Learning: A Self-Administered Intervention That Guides Self-Reflection on Effective Resource Use Enhances Academic Performance. *Psychological Science*, 28(6), 774-785. DOI: 10.1177/0956797617696456

Chi, M. T. H., Glaser, R., & Resse, E. (1981). Expertise in problem solving. In R. J. Sternberg (Ed.), *Advances in the psychology of human intelligence (v. 1)*. Hillsdale, NJ: Erlbaum

Clariana, R. B., Draper, D., & Land, S. M. (2011, November). *An automated measure of group knowledge structure convergence*. Paper presented at the annual meeting of the AECT International Convention, Jacksonville, FL.

Cohen, J (1992). "A power primer". *Psychological Bulletin*. 112 (1): 155–159.

doi:10.1037/0033-2909.112.1.155. PMID 19565683.

Cooke, N. J., Salas, E., Cannon-Bowers, J. A., & Stout, R. (2000). Measuring team knowledge. *Human Factors*, 42, 151–173. DOI: 10.1518/001872000779656561

Craik, K. J. W. (1952). *The nature of explanation*. Cambridge, United Kingdom: Cambridge University Press.

Cress, U., & Hesse, F. W. (2013). Quantitative methods for studying small groups. In C. Hmelo-Silver, C. Chinn, C. Chan, & A. O'Donnell (Eds.), *The international handbook of collaborative learning* (pp. 85–111). New York, NY: Routledge.

- Damon, W., & Phelps, E. (1989). Critical distinctions among three approaches to peer education. *International journal of educational research*, *13*(1), 9-19. DOI: 10.1016/0883-0355(89)90013-X
- Darabi, A. A., Nelson, D. W., & Seel, N. M. (2010). The role of supportive information in the development and progression of mental models. In J.M. Spector, D. Ifenthaler, P. Isaias, Kinshuk, D. Sampson (Eds.), *Learning and instruction in the digital age* (pp. 101-115). New York, NY: Springer.
- Davis, D. C., Gentili, K. L., Trevisan, M. S., & Calkins, D. E. (2002). Engineering design assessment processes and scoring scales for program improvement and accountability. *Journal of Engineering Education*, *91*(2), 211-221.
- de Kleer, J. & Seely Brown, J. (1983). Assumptions and ambiguities in mechanical mental models. In D. Gentner & A.L. Stevens (Eds.), *Mental models* (pp. 155- 190). Hillsdale, New Jersey: Lawrence Erlbaum.
- DeChurch, L. A., & Mesmer-Magnus, J. R. (2010). Measuring shared team mental models: A meta-analysis. *Group Dynamics: Theory, research, and practice*, *14*, 1- 14. DOI: 10.1037/a0017455
- Derry, S. J. (1996). Cognitive schema theory in the constructivist debate. *Educational Psychologist*, *31*, 163-174. DOI: 10.1080/00461520.1996.9653264
- DiDonato, N. C. (2013). Effective self-and co-regulation in collaborative learning groups: An analysis of how students regulate problem solving of authentic interdisciplinary tasks. *Instructional science*, *41*, 25-47. DOI: 10.1007/s11251-012-9206-9

- Dillenbourg, P. (1999). What do you mean by "collaborative learning"? In P. Dillenbourg (Ed.), *Collaborative learning: Cognitive and computational approaches* (pp. 1-16). Amsterdam, NL: Pergamon, Elsevier Science.
- Dillenbourg, P. (2002). Over-scripting CSCL: The risks of blending collaborative learning with instructional design. In P.A. Kirschner (Ed.), *Three worlds of CSCL. Can we support CSCL* (pp. 61-91). Open Universiteit Nederland: Heerlen.
- diSessa (1983). Phenomenology and the evolution of intuition. In D. Gentner & A.L. Stevens (Eds.), *Mental models* (p. 15-33). Hillsdale, NJ: Lawrence Erlbaum.
- Dong, A., Kleinsmann, M. S., & Deken, F. (2013). Investigating design cognition in the construction and enactment of team mental models. *Design Studies, 34*(1), 1-33. DOI: 10.1016/j.destud.2012.05.003
- Dym, C. L., Agogino, A. M., Eris, O., Frey, D. D., & Leifer, L. J. (2005). Engineering design thinking, teaching, and learning. *Journal of Engineering Education, 94*, 103-120. DOI: 10.1002/j.2168-9830.2005.tb00832.x
- Edwards, B. D., Day, E. A., Arthur Jr, W., & Bell, S. T. (2006). Relationships among team ability composition, team mental models, and team performance. *Journal of Applied Psychology, 91*(3), 727. DOI: 10.1037/0021-9010.91.3.727
- Employment and Social Development Canada (2015, September). *Understanding Essential skills* [website]. Retrieved from <https://www.canada.ca/en/employment-social-development/programs/essential-skills/definitions.html>
- Fisher, D. M., Bell, S. T., Dierdorff, E. C., & Belohlav, J. A. (2012). Facet personality and surface-level diversity as team mental model antecedents: implications for implicit

coordination. *Journal of Applied Psychology*, 97(4), 825. Retrieved from  
<http://psycnet.apa.org/buy/2012-08583-001>

Freeman, L. C. (1978). Centrality in social networks conceptual clarification. *Social networks*, 1(3), 215-239. DOI: 10.1016/0378-8733(78)90021-7

Ghosh, D., & Vogt, A. (2012). Outliers: An evaluation of methodologies. In *Joint statistical meetings* (pp. 3455-3460). San Diego, CA: American Statistical Association. Retrieved from  
[http://ww2.amstat.org/sections/srms/proceedings/y2012/Files/304068\\_72402.pdf](http://ww2.amstat.org/sections/srms/proceedings/y2012/Files/304068_72402.pdf)

Glaser, R. (1985). *Thoughts on expertise* (Technical Report No. 8). Pittsburgh, PA: Learning Research and Development Center, University of Pittsburgh.

Glaser, R., & Chi, M. T. H. (1988). Overview. In M. T. H. Chi, R. Glaser, & M. J. Farr (Eds.). *The nature of expertise* (xv-xxviii). Mahwah, NJ: Erlbaum.

Hadwin, A. F. (2006). Do your students really understand your assignment? *LTC Currents Newsletter*, II (3), 1-9. Retrieved from <http://cgi.stanford.edu/~dept-ctl/tomprof/posting.php?ID=857>

Hadwin, A. F. (2017, August). *Promoting adaptive regulation*. Keynote at the European Association for Research on Learning and Instruction, Tampere, Finland. Retrieved from  
<https://youtu.be/DHD8loVaTQI>

Hadwin, A. F., Järvelä, S., & Miller, M. (2011). Self-regulated, co-regulated, and socially shared regulation of learning. In B. J. Zimmerman, & D. H. Schunk, (Eds.), *Handbook of self-regulation of learning and performance* (pp. 65–84). New York, NY: Routledge.

- Hadwin, A. F., Järvelä, S., & Miller, M. (2017). Self-regulation, co-regulation, and shared regulation in collaborative learning environments. In D. H. Schunk, & J. A. Greene, (Eds.). *Handbook of self-regulation of learning and performance (2nd ed.)*. (pp. 83 - 106). New York: Routledge.
- Hadwin, A. F., Nesbit, J. C., Jamieson-Noel, D., Code, J., & Winne, P. H. (2007). Examining trace data to explore self-regulated learning. *Metacognition and Learning, 2*(2-3), 107-124.
- Hambrick, D. Z., & Hoffman, R. R. (2016). Expertise: A Second Look. *IEEE Intelligent Systems, 31*(4), 50-55. DOI: 10.1109/MIS.2016.69
- Hart Research (2015). *Falling Short? College Learning and Career Success: Selected findings from online surveys of employers and college students conducted on behalf of the Association of American Colleges & Universities*. Washington, DC.: Author. Retrieved from <https://www.aacu.org/leap/public-opinion-research/2015-survey-results>
- Howell, D. C. (2008). *Fundamental statistics for the behavioral sciences*. Toronto, ON: Thomson Wadsworth.
- Järvelä, S., & Hadwin, A. F. (2013). New frontiers: Regulating learning in CSCL. *Educational Psychologist, 48*, 25-39. DOI: 10.1080/00461520.2012.748006
- Janssen, J., Cress, U., Erkens, G., & Kirschner, P. (2013). Multilevel analysis for the analysis of collaborative learning. In C. Hmelo-Silver, C. Chinn, C. Chan, & A. O'Donnell (Eds.), *The international handbook of collaborative learning* (pp. 112-124). New York, NY: Routledge.

- Jeong, H., & Chi, M. T. (2007). Knowledge convergence and collaborative learning. *Instructional Science*, 35, 287-315. DOI: 10.1007/s11251-006-9008-z
- Johnson, D. W., & Johnson, R. T. (1999). *Learning together and alone: Cooperative competitive and individualistic learning* (5th ed.). Boston, MA: Allyn & Bacon.
- Johnson, D.W., & Johnson, R.T. (1989). *Cooperation and competition: Theory and research*. Edina, MN: Interaction Book Company.
- Johnson, T. E., & Lee, Y. (2008). The relationship between shared mental models and task performance in an online team-based learning environment. *Performance Improvement Quarterly*, 21(3), 97-112. DOI: 10.1002/piq.20033
- Johnson-Laird, P.N. (1983). *Mental models: Towards a cognitive science of language, inference, and consciousness*. Cambridge, United Kingdom, Cambridge University Press.
- Johnson-Laird, P.N. (1989). Mental models. In M.I. Posner (Ed). *The foundations of cognitive science* (pp.469 - 499). Boston, MA: MIT Press.
- Jones, N. A., Ross, H., Lynam, T., Perez, P. & Leitch, A. (2011). Mental models: An interdisciplinary synthesis of theory and methods. *Ecology and Society*, 16 (1), 46-46. Retrieved from <http://www.ecologyandsociety.org/vol16/iss1/art46/>
- Kadushin, C. (2012). *Understanding social networks: Theories, concepts, and findings*. Toronto, Ontario: Oxford University Press.

- Kim, K., & Clariana, R. B. (2015). Knowledge structure measures of reader's situation models across languages: Translation engenders richer structure. *Technology, Knowledge and Learning, 20*(2), 249-268. DOI: 10.1007/s10758-015-9246-8
- Klimoski, R., & Mohammed, S. (1994). Team mental model: Construct or metaphor. *Journal of Management, 20*(2), 403-437. DOI: 10.1177/014920639402000206
- Kuhn, D. (2000). Metacognitive development. *Current directions in psychological science, 9*(5), 178-181.
- Lan, W. Y. (1996). The effects of self-monitoring on students' course performance, use of learning strategies, attitude, self-judgment ability, and knowledge representation. *The Journal of Experimental Education, 64*(2), 101-115.
- Lan, W. (2005). Self-monitoring and its relationship with educational level and task importance. *Educational psychology, 25*(1), 109-127.
- Langan-Fox, J., Code, S., & Langfield-Smith, K. (2000). Team mental models: Techniques, methods, and analytic approaches. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 42*(2), 242-271. DOI: 10.1518/001872000779656534
- Lee, M., & Johnson, T. E. (2008). Understanding the effects of team cognition associated with complex engineering tasks: Dynamics of shared mental models, Task-SMM, and Team-SMM. *Performance Improvement Quarterly, 21*(3), 73-95. DOI: 10.1002/piq.20032
- Lim, B. C., & Klein, K. J. (2006). Team mental models and team performance: A field study of the effects of team mental model similarity and accuracy. *Journal of Organizational Behavior, 27*(4), 403-418. DOI: 10.1002/job.387

- Mathieu, J. E., Heffner T.S., Goodwin, G.F., Cannon-Bowers J.A., & Salas, E. (2005). Scaling the quality of teammates' mental models: Equifinality and normative comparisons. *Journal of Organizational Behavior*, 26, 37-56. DOI: 10.1002/job.296
- Mathieu, J. E., Heffner, T. S., Goodwin, G. F., Salas, E., & Cannon-Bowers, J. A. (2000). The influence of shared mental models on team process and performance. *Journal of Applied Psychology*, 85, 273-283. DOI: 10.1037/0021-9010.85.2.273
- MATLAB (2015b) [Computer software]. Natick, MA: MathWorks.
- McGuire, Li, & Gebali (2015, June). *Teaching design to first-year engineering students*. Proceedings of the 2015 Canadian Engineering Education Association (CEEA15) Conference, McMaster University, Hamilton, Ontario.
- Miller, M. (2015). *Leveraging CSCL technology for supporting and researching shared task perceptions in socially shared regulation of learning* (unpublished doctoral dissertation). University of Victoria, Victoria, B.C.
- Miller, M., & Hadwin, A. (2015). Scripting and awareness tools for regulating collaborative learning: Changing the landscape of support in CSCL. *Computers in Human Behavior*, 52, 573–588. doi:10.1016/j.chb.2015.01.050
- Miller, M., Hadwin, A. F., & Starcheski, S. (2017, May). Group Awareness Tools for Strategic Planning in Collaboration. In *Promoting Adaptive Regulation in Collaborative Learning Contexts*. Symposium conducted at the annual conference of the Canadian Society for the Study of Education, Toronto, ON.

- Milliken, F. J., Bartel, C. A., & Kurtzberg, T. R. (2003). Diversity and creativity in work groups: A dynamic perspective on the affective and cognitive process that link diversity and performance. In P. B. Paulus & B. A. Nijstad, *Group creativity: Innovation through collaboration* (pp. 32-62). Toronto, ON: Oxford University Press.
- Moazzen, I., Miller, M., Wild, P., Jackson, L., & Hadwin, A. F. (2014, June). *Engineering design survey*. Proceedings of the 2014 Canadian Engineering Education Association (CEEA14) Conference, Canmore, AB. Retrieved from <http://ojs.library.queensu.ca/index.php/PCEEA/article/view/5892>
- Mohammed, S., Ferzandi, L., & Hamilton, K. (2010). Metaphor no more: A 15-year review of the team mental model construct. *Journal of Management*, *36*, 876-910. DOI: 10.1177/0149206309356804
- Mohammed, S., Klimoski, R., & Rentsch, J. R. (2000). The measurement of team mental models: We have no shared schema. *Organizational Research Methods*, *3*, 123-165. DOI: 10.1177/109442810032001
- Newman, M.E.J. (2010). *Networks: An introduction*. Toronto, Ontario: Oxford University Press.
- Panadero, E. (2017). A review of self-regulated learning: six models and four directions for research. *Frontiers in psychology*, *8*, 422.
- Passow, H. J. (2012). Which ABET competencies do engineering graduates find most important in their work? *Journal of Engineering Education*, *101*(1), 95-118. DOI: 10.1002/j.2168-9830.2012.tb00043.x

Pathfinder (Version 9.0) [Computer software]. Las Cruces, NM: Interlink.

Pintrich, P. R., & Schrauben, B. (1992). Students' motivational beliefs and their cognitive engagement in classroom academic tasks. In D. H. Schunk & J. L. Meece (Eds.), *Student perceptions in the classroom* (pp. 149-183). New York, NY: Routledge.

Pintrich, P.R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P.R. Pintrich & M. Zeidner (Eds.), *Handbook of Self-regulation* (p. 451 – 502). San Diego, CA: Academic Press.

Premier's Technology Council of British Columbia (2010). A vision for 21st century education. Retrieved: [http://www.gov.bc.ca/premier/attachments/PTC\\_vision%20for\\_education.pdf](http://www.gov.bc.ca/premier/attachments/PTC_vision%20for_education.pdf)

Puustinen, M., & Pulkkinen, L. (2001). Models of self-regulated learning: A review. *Scandinavian Journal of Educational Research*, 45(3), 269-286. DOI: 10.1080/00313830120074206

Rasmussen, J. (1979). On the structure of knowledge—A morphology of mental models in a man-machine system context (Tech. Rep. No. Riso-M-2192). Roskilde, Denmark: Riso National Laboratory.

Resick, C. J., Dickson, M. W., Mitchelson, J. K., Allison, L. K., & Clark, M. A. (2010a). Team composition, cognition, and effectiveness: Examining mental model similarity and accuracy. *Group Dynamics: Theory, Research, and Practice*, 14(2), 174. Retrieved from <http://psycnet.apa.org/buy/2010-10961-007>

- Resick, C. J., Murase, T., Bedwell, W. L., Sanz, E., Jiménez, M., & DeChurch, L. A. (2010b). Mental model metrics and team adaptability: A multi-facet multi-method examination. *Group Dynamics: Theory, Research, and Practice, 14*(4), 332. Retrieved from <http://psycnet.apa.org/buy/2010-25392-005>
- Rook, L. (2013). Mental models: A robust definition. *The Learning Organization, 20*, 38-47. DOI: 10.1108/09696471311288519
- Roschelle, J., & Teasley, S. D. (1995, January). The construction of shared knowledge in collaborative problem solving. In C. O'Malley (Ed.), *Computer supported collaborative learning: NATO Advanced Sciences Institute [ASI] Series Vol. 128* (pp. 69-97). Berlin, Germany: Springer.
- Ross, S., & Allen, N. (2012). Examining the convergent validity of shared mental model measures. *Behavior research methods, 44*(4), 1052-1062. DOI: 10.3758/s13428-012-0201-5
- Rouse, W. B., & Morris, N. M. (1986). On looking into the black box: Prospects and limits in the search for mental models. *Psychological Bulletin, 100*, 349. Retrieved from <http://psycnet.apa.org/buy/1987-09358-001>
- Rowe, A. L., & Cooke, N. J. (1995). Measuring mental models: Choosing the right tools for the job. *Human resource development quarterly, 6*(3), 243-255. DOI: 10.1002/hrdq.3920060303
- Sætrevik, B., & Eid, J. (2014). The "Similarity Index" as an Indicator of Shared Mental Models and Situation Awareness in Field Studies. *Journal of Cognitive Engineering and Decision Making*, DOI: 1555343413514585.

- Salas, E., Rosen, M., Burke, C. S., & Goodwin, G. F. (2009). The wisdom of collectives in organizations: An update of the teamwork competencies. In E. Salas, G. F. Goodwin, & C. S. Burke (Eds.), *Team effectiveness in complex organizations: cross-disciplinary perspectives and approaches* (pp. 39–79). New York, NY: Taylor & Francis.
- Salas, E., Sims, D. E., & Burke, C. S. (2005). Is there a “Big Five” in teamwork? *Small group research*, 36(5), 555-599. DOI: 10.1177/1046496405277134
- Santos, C.M., & Passos, A.M. (2013). Team mental models, relationship conflict and effectiveness over time. *Team Performance Management*, 19(7/8), 363-385. DOI: 10.1108/TPM-01-2013-0003
- Schvaneveldt, R.W. (1990). Preface. In R.W. Schvaneveldt, (Ed.), *Pathfinder associative networks: Studies in knowledge organization*, (pp. ix – xi). Norwood, NJ: Ablex. ISBN [9780893916244](https://doi.org/10.1300/J089n0101)
- Scott, G., & Yates, K. W. (2002). Using successful graduates to improve the quality of undergraduate engineering programmes. *European journal of engineering education*, 27(4), 363-378. DOI: 10.1080/03043790210166666
- Seel, N. M. (2001). Epistemology, situated cognition, and mental models: 'Like a bridge over troubled water'. *Instructional science*, 29(4-5), 403-427. DOI: 10.1023/A:1011952010705
- Shuman, L. J., Besterfield-Sacre, M., & McGourty, J. (2005). The ABET “professional skills”— Can they be taught? Can they be assessed? *Journal of engineering education*, 94(1), 41-55. DOI: 10.1002/j.2168-9830.2005.tb00828.x

- Smith-Jentsch, K. A., Cannon-Bowers, J. A., Tannenbaum, S. I., & Salas, E. (2008). Guided team self-correction: Impacts on team mental models, processes, and effectiveness. *Small Group Research, 39*(3), 303-327. DOI: 10.1177/1046496408317794
- Starcheski, S., Davis, S. K., Bakhtiar, A., Webster, E., Miller, M., & Hadwin, A. F. (2017, May). Processes and targets of regulation in online collaboration. In *Promoting Adaptive Regulation in Collaborative Learning Contexts*. Symposium conducted at the annual conference of the Canadian Society for the Study of Education, Toronto, ON.
- Stout, R. J., Cannon-Bowers, J. A., Salas, E., & Milanovich, D. M. (1999). Planning, shared mental models, and coordinated performance: An empirical link is established. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 41*, 61-71. DOI: 10.1518/001872099779577273
- Tabachnick, B. G., & Fidell, L. S. (2001). *Using Multivariate Statistics*. Toronto, ON: Pearson.
- University of Victoria Calendar 2016-2017 (2016, September). Retrieved from the University of Victoria website: <http://web.uvic.ca/calendar2016-05/cal/uvic/learning-outcomes.html>
- Van den Bossche, P., Gijssels, W., Segers, M., Woltjer, G., & Kirschner, P. (2011). Team learning: building shared mental models. *Instructional Science, 39*(3), 283-301. DOI: 10.1007/s11251-010-9128-3
- Warner, R. (2013). *Applied statistics: From bivariate through multivariate techniques*. Los Angeles, CA: Sage.

- Winne, P. H. (1997). Experimenting to bootstrap self-regulated learning. *Journal of Educational Psychology, 89*, 397 - 410. Retrieved from <http://psycnet.apa.org/buy/1997-05647-001>
- Winne, P. H. (2011). A cognitive and metacognitive analysis of self-regulated learning. In B. J. Zimmerman, & D. H. Schunk, (Eds.), *Handbook of self-regulation of learning and performance* (pp. 15-32). New York, NY: Routledge.
- Winne, P. H. (2017). Cognition and Metacognition Within Self-Regulated Learning. In D. H. Schunk, & J. A. Greene, (Eds.). *Handbook of self-regulation of learning and performance (2nd ed.)*. (pp. 36 - 48). New York: Routledge.
- Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated engagement in learning. In D. Hacker, J. Dunlosky, & A. Graesser (Eds.), *Metacognition in Educational Theory and Practice* (pp. 277-304). Hillsdale, NJ: Lawrence Erlbaum.
- Winne, P., Hadwin, A. F., & Perry, N. E. (2013). Metacognition and computer- supported collaborative learning. In C. E. Hmelo-Silver, A. O'Donnell, C. Chan, & C. Chinn, (Eds.), *International handbook of collaborative learning*. (pp. 462-479). New York, NY: Taylor & Francis.
- Zimmerman, B. J. (1986). Development of self-regulated learning: Which are the key subprocesses? *Contemporary Educational Psychology, 11*, 301-313. DOI: 10.1016/0361-476X(86)90027-5
- Zimmerman, B. J. (1989). A social cognitive view of self-regulated academic learning. *Journal of Educational Psychology, 81*, 329–339. doi: 10.1037/0022-0663.81.3.329

---

## Appendix A: Participant Consent Form

---



UVic

Department of Educational  
Psychology & Leadership  
Studies

*Participant  
Consent Form*



Technology Integration and  
Evaluation Research Lab

---

### Exploring Teamwork in Engineering Design

Principal Investigators

Dr. Allyson Hadwin ([Hadwin@uvic.ca](mailto:Hadwin@uvic.ca))

Dr. Peter Wild ([pwild@uvic.ca](mailto:pwild@uvic.ca))

This research is funded by two national grants: (1)NSERC--*Chair in Design Engineering at the University of Victoria grant* (2) SSHRC-- *Promoting Adaptive Regulation for 21st Century Success (PAR-21) grant*. Researchers coordinating this survey include: Dr. Peter Wild ([pwild@uvic.ca](mailto:pwild@uvic.ca)), Dr. Allyson Hadwin ([Hadwin@uvic.ca](mailto:Hadwin@uvic.ca)), Dr. LillAnne Jackson, Engineering Associate Dean Undergraduate programs, and Margaret Gwyn, Engineering projects coordinator.

#### **Purpose and objectives**

As part of improving instruction in the Engineering department, we are researching students' experiences in their design projects. Specifically, we aim to:

- Understand how undergraduate Engineering students develop design knowledge and expertise
- Understand the challenges students face in their undergraduate design work
- Inform evidence-based decision making about design instruction and program development
- Inform theory and research about engineering design and effective teamwork.

#### **Importance of this research**

- This research will help members of the UVic community and the broader scholarly community to understand affordances and barriers in students' development of design competencies.

#### **Participating in this research involves:**

- Completing a short questionnaire about your experiences in your last design project
- Allowing researchers to access institutionally collected DATA for research purposes (E.G. UNIVERSITY AND HIGH SCHOOL GPA, COURSE ENROLLMENT RECORDS, DISCIPLINE AND PROGRAM) throughout your undergraduate degree
- Allowing researchers to access grades for relevant coursework (E.G. DESIGN PROJECT GRADE, GRADES ON DESIGN PROJECT DELIVERABLES) and the names of your group members during group work in this course.
- Please be advised that Fluid Survey (an online survey tool) used for this research is located in the U.S. As such, there is a possibility that information about you may be accessed without your knowledge or consent by the U.S. government in compliance with the U.S. Patriot Act.

### **Inconvenience, risks, & benefits**

- The only inconvenience will be the time you spend completing the questionnaire (approx. 15 mins – 20 mins).
- There are no known or anticipated risks associated with this research.
- Potential benefits include reflecting on your design skills and how to improve them and contributing to program development and scholarly research on this topic.

### **Researchers relationship with participants**

- Dr. LillAnne Jackson, Engineering Associate Dean Undergraduate Programs (Principal Investigator) will not know you are participating in this research. All names and identifying information will be removed before releasing data to Dr. Jackson.
- Your course instructor will not know who has consented to participate or have access to the data until after the course is complete and final grades have been submitted.

### **Participation is voluntary; You can withdraw at anytime**

- You are being asked to participate because you are an undergraduate student enrolled in a course containing a design work component/assignment in the Faculty of Engineering.
- **If indicated by your course instructor**, you may choose to complete the survey in order to receive a bonus mark in your current design course, but decline consent to participate in this research. Your course instructor will receive a list of students who have completed the questionnaire in order to provide the bonus marks. Your course instructor will not know if you are participating in this research nor have access to your individual responses.
- Your participation in this research is completely voluntary. THERE WILL BE NO NEGATIVE CONSEQUENCES FOR STUDENTS WHO CHOOSE NOT TO PARTICIPATE.
- If you decide to participate, you can withdraw at any time without any consequences or explanation. If you do withdraw from the study, your data will not be included analysis.

### **Anonymity and confidentiality**

- Questionnaires and institutional data with your name or student ID are not anonymous.
- However, your confidentiality will be protected by (1) replacing your name and identifying information with a random case number, and (2) summarizing data across many students. WHEN SPECIFIC EXAMPLES ARE USED, NAMES WILL BE REPLACED WITH PSEUDONYMS AND ALL REFERENCES TO SPECIFIC PEOPLE, COURSES, AND ASSIGNMENTS WILL BE REMOVED.

### **What will happen to data and how will findings be shared?**

- ALL data will be stored on a password protected server or locked filing cabinet only accessible to the researchers. DATA will be stored for 10 years, after which electronic data will be erased and paper copies will be shredded.
- Data will be analyzed by the principal investigators and research collaborators. Data may also be analyzed by the principal investigators and their research collaborators as part of the engineering program accreditation process for the Canadian Engineering Accreditation Board (CEAB). Data may also be analyzed by other researchers for purposes such as for MA theses and Doctoral dissertations. Any data provided to other researchers will be fully anonymous and include no identifying information. Findings

will be presented through academic publications/presentations, research websites (<http://allysonhadwin.wordpress.com/>), student theses and dissertations, and reports to university administrators.

### **Contacts**

If you have any questions regarding this study or wish to withdraw at any time, you may contact DR. ALLYSON HADWIN, FACULTY OF EDUCATION (250.721.6347 OR [HADWIN@UVIC.CA](mailto:HADWIN@UVIC.CA)). IN CASE OF QUESTIONS AND CONCERNS, YOU MAY ALSO CONTACT Dr. Tom Tiedje, Dean of Engineering (250.721.8612 or [enrdean@uvic.ca](mailto:enrdean@uvic.ca)).

- Note: Do not contact Dr. LillAnne Jackson because she is Engineering Associate Dean, Undergraduate Programs and cannot know which students are participating. If you are enrolled in ENGR 110/112 do not contact Dr. Peter Wild because he is a course instructor and cannot know which students are participating until course grades are submitted.

You may verify the ethical approval of this study, or raise any concerns you might have, by contacting:

- Human Research Ethics Office at UVic (250.472.4545 or [ethics@uvic.ca](mailto:ethics@uvic.ca))

### **Consent**

Clicking on YES below indicates that you understand the above conditions of participation in this study and that you have had the opportunity to have your questions answered by the researchers, and that you consent to participate in this research project.

I consent to participate in the research:

Yes  No

You must provide your full name in order to receive any bonus marks:

Name: \_\_\_\_\_ Date: \_\_\_\_\_ Student number: \_\_\_\_\_

## Appendix B: Mental Model Reflection Tool

### Exploring Teamwork in Engineering Design

This survey will take approximately 15-20 mins to complete.

There are elements in this survey that are not mobile friendly. Please complete the survey via computer.

1. Age:

- Below 17     17 to 20     21 to 30     31 to 40     Over 40

2. Sex:

- Male     Female     Other     Do not wish to disclose

3. Year of program:

- 1<sup>st</sup> year     2<sup>nd</sup> year     3<sup>rd</sup> year     4<sup>th</sup> year or higher

4. Name of course in which you received this survey:

---

5. Program or intended program:

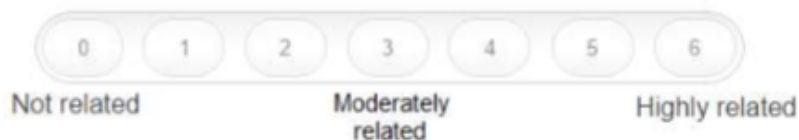
- |                                     |                                                         |
|-------------------------------------|---------------------------------------------------------|
| <input type="checkbox"/> Electrical | <input type="checkbox"/> Biomedical                     |
| <input type="checkbox"/> Computer   | <input type="checkbox"/> Civil                          |
| <input type="checkbox"/> Software   | <input type="checkbox"/> Other, please specify... _____ |
| <input type="checkbox"/> Mechanical |                                                         |

6. Name and briefly describe the most recent design project you completed in this course:

## Instructions

On the next two pages, you will be presented with ideas related to **teamwork** and **design**. Your task is to judge how related each idea is to each of the other ideas. **You should base your judgments on how you believe the ideas work together to help you successfully design as a team.**

The ideas will be presented on the screen in a matrix. Each drop-down block asks you to compare the two ideas. Please indicate how related these ideas are using the drop-down scale provided. You can think of the points along the scale as representing degrees of relatedness ranging from 0 (not related) to 6 (highly related).



**The examples below show you how to use the response scale.**

*This answer (6) means these concepts are HIGHLY related. I chose this answer because I believe that there is a strong relationship between “talking to friends” and “being happy”.*

Example:

	Talking to friends.	Being happy.
Being happy.	6 (highly related) ▼	
Watching movies.	---	---

*This answer (0) means these concepts are NOT related. I chose this answer because I believe that there is no relationship between “talking to friends” and “watching movies”. I do not talk to my friends when I am watching movies.*

Example:

	Talking to friends.	Being happy.
Being happy.	---	
Watching movies.	0 (not related) ▼	---

*This answer (3) means these concepts are MODERATELY related. I chose this answer because I believe that there is a moderate relationship between “being happy” and “watching movies”. Movies make me happy, but there are other things that make me happier.*

Example:

	Talking to friends.	Being happy.
Being happy.	---	
Watching movies.	---	3 (moderately related)

After completing my matrix, it looks like this...

Example:

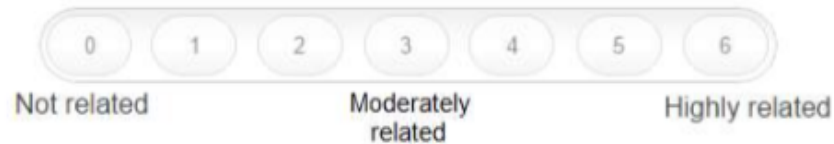
	Talking to friends.	Being happy.
Being happy.	6 (highly related)	
Watching movies.	0 (not related)	3

**Let's get started!**

### Instructions

You should base your judgments on how you believe the ideas work together to help you successfully design as a team.

Each drop-down block asks you to compare the two ideas. Please indicate how related these ideas are using the drop-down scale provided. You can think of the points along the scale as representing degrees of relatedness ranging from 0 (not related) to 6 (highly related).



#### Teamwork Processes: Part 1 / 2

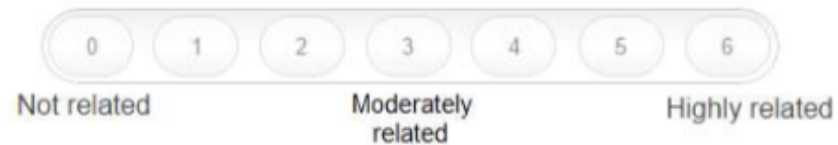
	Agree on what the task requires.	Negotiate shared goals, roles, and plans.	Work together to adjust plans as needed.	Monitor project progress and team performance.	Foster positive team climate.	Make full use of each person's knowledge and skills.	Fulfill roles and responsibilities.
Negotiate shared goals, roles, and plans.							
Work together to adjust plans as needed.							
Monitor project progress and team performance.							
Foster positive team climate.							
Make full use of each person's knowledge and skills.							
Fulfill roles and responsibilities.							
Perform effectively as a team.							

Please scroll to the right to complete all columns before clicking next!

### Instructions

You should base your judgments on how you believe the ideas work together to help you successfully design as a team.

Each drop-down block asks you to compare the two ideas. Please indicate how related these ideas are using the drop-down scale provided. You can think of the points along the scale as representing degrees of relatedness ranging from 0 (not related) to 6 (highly related).



#### Design Processes: Part 2/2

	Assess client needs.	Define problem (criteria, constraints, objectives/goals, requirements).	Identify and assess background information.	Generate and evaluate alternative design concepts.	Perform detailed design engineering and analysis.	Implement, test and refine detailed design.
Define problem (criteria, constraints, objectives/goals, requirements).						
Identify and assess background information.						
Generate and evaluate alternative design concepts.						
Perform detailed design engineering and analysis.						
Implement, test and refine detailed design.						
Document detailed design and supporting analysis.						

Please scroll to the right to complete all columns before clicking next!



**Design Processes**

	1	2	3	4	5	6	N/A
Assess client needs.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Define problem (criteria, constraints, objectives/goals, requirements).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Identify and assess background information.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Generate and evaluate alternative design concepts.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Perform detailed design engineering and analysis.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Implement, test and refine detailed design.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Document detailed design and supporting analysis.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>



Thank you for taking the time to complete this survey.

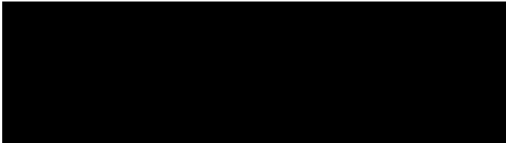
If you have any questions regarding this study or wish to withdraw at any time, you may contact DR. ALLYSON HADWIN, FACULTY OF EDUCATION (250.721.6347 OR HADWIN@UVIC.CA).

## Appendix C: Ethics Certification



Office of Research Services | Human Research Ethics Board  
 Michael Williams Building Rm B202 PO Box 1700 STN CSC Victoria BC V8W 2Y2 Canada  
 T 250-472-4545 | F 250-721-8960 | ethics@uvic.ca | uvic.ca/research |

### Certificate of Renewed Approval

<b>PRINCIPAL INVESTIGATOR:</b> Peter Wild <b>UVic STATUS:</b> Faculty <b>UVic DEPARTMENT:</b> MENG	<b>ETHICS PROTOCOL NUMBER:</b> 13-296 Minimal Risk Review - Delegated <b>ORIGINAL APPROVAL DATE:</b> 29-Aug-13 <b>RENEWED ON:</b> 02-Aug-17 <b>APPROVAL EXPIRY DATE:</b> 28-Aug-18
<b>PROJECT TITLE:</b> Design Experiences in Engineering  <b>RESEARCH TEAM MEMBER</b> Co-principal Investigators: Allyson Hadwin (UVic), LillAnne Jackson (UVic); Co-Investigators: Margaret Gwyn (UVic), Iman Moazzen (UVic), Todd Milford (UVic); Research Assistant: Rebecca Edwards  <b>DECLARED PROJECT FUNDING:</b> NSERC; SSHRC	
<b>CONDITIONS OF APPROVAL</b>	
<p>This Certificate of Approval is valid for the above term provided there is no change in the protocol.</p> <p><b>Modifications</b>          To make any changes to the approved research procedures in your study, please submit a "Request for Modification" form. You must receive ethics approval before proceeding with your modified protocol.</p> <p><b>Renewals</b>          Your ethics approval must be current for the period during which you are recruiting participants or collecting data. To renew your protocol, please submit a "Request for Renewal" form before the expiry date on your certificate. You will be sent an emailed reminder prompting you to renew your protocol about six weeks before your expiry date.</p> <p><b>Project Closures</b>          When you have completed all data collection activities and will have no further contact with participants, please notify the Human Research Ethics Board by submitting a "Notice of Project Completion" form.</p>	
<h2>Certification</h2>	
<p>This certifies that the UVic Human Research Ethics Board has examined this research protocol and concluded that, in all respects, the proposed research meets the appropriate standards of ethics as outlined by the University of Victoria Research Regulations Involving Human Participants.</p> <div style="text-align: center;">         Associate Vice-President Research Operations     </div>	

Certificate Issued On: 02-Aug-17

13-296 Wild, Peter