Title
A Descriptive Study of Learning Style Diversity in Design and Innovation Teams

Author
Lau, Kimberly

Publication Date
2015

Peer reviewed|Thesis/dissertation

A Descriptive Study of Learning Style Diversity in Design and Innovation Teams

by

Kimberly Lau

A dissertation submitted in partial satisfaction of the
requirements for the degree of
Doctor of Philosophy

in

Engineering – Mechanical Engineering

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Alice M. Agogino, Chair
Professor Sara L. Beckman
Professor Dennis K. Lieu

Summer 2015

A Descriptive Study of Learning Style Diversity in
Design and Innovation Teams

by

Kimberly Lau

Abstract

A Descriptive Study of Learning Style Diversity in
Design and Innovation Teams

by

Kimberly Lau

Doctor of Philosophy in Engineering – Mechanical Engineering

University of California, Berkeley

Professor Alice M. Agogino, Chair

Design and innovation are increasingly important for attaining competitive advantage. This is achieved largely through the creation of meaningful customer experiences, and companies employing cross-functional teams are consistently reaching the best results. Designing these customer experiences requires teamwork that capitalizes on the diversity of the design team – whether gender, functional, disciplinary or cognitive. This research investigates the role of diversity in design teams, and in particular the role of cognitive diversity. It leverages David Kolb's experiential learning theory and associated learning styles because they correlate well with the phases of the design process. It also considers factors such as gender, ethnicity, discipline, and job level.

The first study explores the composition of innovation- or design-oriented populations in academic and corporate settings. Data was gathered from undergraduate-level and graduate-level students as well as from industry professionals in design, engineering, and consulting firms worldwide. The analysis draws comparisons among the international populations, across fields of expertise, and with other demographics to build a characterization of the design population. The findings show a surprising lack of diversity where it might be most expected. In particular, converging learners consistently dominate across all populations, highlighting an alarming absence of diverging learners in the design world.

The second study explores the confidence levels in ABET skills and learning style preferences of students in project-based design courses. Results highlight national and gender differences in students' perception of their development in ABET-related engineering and design skills. American students rated themselves higher in creativity, teamwork, ethics, facility with tools of engineering practice, and in recognizing global impact. Korean students assessed their skills higher in design, problem solving, and communication skills. However, the students follow similar gender patterns overall, where men reported more confidence in technical and analytical skills and women were more confident in communication and teamwork skills. The results also show behavioral trends that match the various learning styles. Accommodators self-rated highest in leadership and management skills, convergers self-ranked their analytical skills as strongest among all other skills, and assimilators perceive themselves as best in data processing.

The third study explores the role of diversity in design team performance and presents results about how diversity factors affect the dynamics and success of a design team. Discipline and gender are also considered. The data were gathered over two semesters of a multidisciplinary, project-based graduate level design course and captured through a series of surveys administered throughout the semester. Results offer insights into how students with different learning styles contribute differently to design team performance. The more diverse teams, as measured by the number of converging learners on the team, generally performed better than homogeneous teams, both in self-perceptions of team performance and by external reviews.

To Mom, for her unconditional and everlasting support.

Table of Contents

List of Figures

List of Tables

Acknowledgements

There are many people to whom I owe thanks for helping to shepherd me to the finish line. First and foremost, I would like to express my gratitude to my committee members.

Alice, my advisor, thank you for your belief and trust in me, and for your unwavering support as I paused one dream to pursue another. I could not have done this without you and your brilliant ideas, advice, consideration, leadership, and passion.

Sara, my unofficial advisor, your mentorship has meant so much to me. Thank you for always making time to talk and work regardless of time zones. You were pivotal in keeping me on the right path, from your guidance on the research to general life chats to your thoughtful edits on this dissertation and beyond.

Dennis, you were the catalyst that first sparked my interest in research. Thank you for believing in me as an undergrad and most especially, for the wonderful years of guidance and friendship that have followed.

I would also like to thank my Berkeley comrades.

Debbie, what a wonderful decade of academic pursuits, race adventures, and long-distance calls. Thank you for loaning your jet pack to me.

Lora, thanks for all the great design chats and collaborations. I can always count on you for thought provoking discussions and fun times.

Heather, Sara, and so many others, thank you for the encouragement and support near and far. It was an honor to watch you all continue on exciting paths, and to follow in your footsteps. Thanks especially to Yawo and Shareena, who never forgot that I was almost done and pushed me to completion.

To my Disney family, who provided an endless stream of encouragement.

Mark, never did I imagine that I could end up creating magic 3,000 miles away from home. Working on your team has been a dream and a privilege. Thank you for your support as I juggled school and work.

Eliana, you are wise beyond your years. Thank you for always checking in with me, and for reminding me of what really matters.

Natalie, Dan, Eric, Dave, Mike, and countless others in D&E, Maingate, and around the parks, thank you for cheering me on always and believing in my skills both at work and in school. Your messages are well received and invaluable on both the brightest and hardest days.

Lastly, to my family, who are always with me.

Thank you for being my most constant cheerleaders, and for always letting me pursue my dreams, wherever in the world they take me. I am where I am today purely because of your love and support.

Didi, my thought partner, you have a clarity of mind beyond your years. Thank you for always challenging me to think creatively and practically. You are the biggest foo of all, and now it's in print.

Nel, you are my role model. Thank you for all the chats, for the advice, and for always keeping me energized and ambitious. Your enthusiasm drives me in everything I do.

Dad, thanks for all the support. Your 'best friend' has made it with your help.

Mom, you are so integral to my success. Thanks for the tangibles: all the meals, chats, your meticulous work on this dissertation, and more. And thanks especially for the intangibles: your unconditional support and pride in all my pursuits, regardless of what I do and when I do it.

Chapter 1

Introduction

The development of new products, solutions, and experiences[1] for end customers is the primary driver of growth for many organizations. New products contribute over 30% of revenues and profits for the average company and over 50% of revenues and profits in the technology sector (Griffin, 1997). Thus, managing the process of designing, developing, and delivering new products, services, and customer experiences is core to competitive success.

Good design in turn requires good teamwork, as no individual can complete the process alone. Multi-disciplinary teams appear as a core success factor in design and innovation in a number of studies on success and failure of new products (Curnow & Moring, 1968), (Zirger & Maidique, 1990), (Wilson, 1994). More broadly, contemporary organizations depend on cross-disciplinary collaboration and flattened hierarchies to achieve continuous innovation and to harness creativity (Edmonson, 2012). Bradley and Hebert (1997) find that cross-functional teams are at the forefront of the "quest for innovative solutions". In today's organizations, "challenges must be approached by people working together across disciplines" due to the increasing uniqueness of today's problems (Edmondson, 2012). As a result, there is increased examination of how to optimize teamwork for performance (Kozlowski et. al, 1999), (Bell, 2007) and innovation (Ancona, 2007).

Diversity is an inherent characteristic of design and innovation teams. They require integration of knowledge from across the functional areas in a typical firm: operations, research and development, and marketing. The challenge in bringing those disparate disciplines together is that with different perspectives comes conflict and tension. Diverse teams have been shown to both significantly under-perform and over-perform more homogeneous teams (Ely & Thomas, 2001). The direction depends on whether the team has a learning perspective that allows them to leverage the information available to them (over-perform), or whether they ignore the diversity or apply biases in interpreting others' inputs (under-perform). Team diversity is most beneficial when the variables of diversity align with the specific task to be performed (Bell et. al, 2011). For instance, a team with greater cognitive diversity may perform better on thinking activities. Williams and O'Reilly (1998) find that people prefer to work in more homogeneous teams, but diversity inherently provides opportunity in the form of different perspectives.

---

[1] In their book "Experience Economy", Pine and Gilmore (1999) describe the stages of evolution through which companies have gone from extracting commodities to making goods to delivering services to staging experiences to guiding transformations. They argue that companies have evolved by increasing the degree of differentiation and customization of what they deliver to customers. In this dissertation, the term "product" refers to this larger trajectory; the design teams studied could be designing physical products, services, customer experiences or transformations.

Individual differences, be they cultural, experiential, or cognitive, cause people to approach a single situation in various ways. Bell et. al (2001) examines various diversity types to find what relationships may emerge within a diverse team. Bunderson and Sutcliffe (2002) explored functional diversity and determined that a team with diverse expertise will perform differently based on how much expertise each member has in their respective function. It is important to note that diversity can also be moderated; for instance, age diversity can be mediated by a team's engagement in highly cognitive activities (Kearney, 2009). The best performing teams are often diverse teams with members that can capitalize on the diversity they have (Ely & Thomas, 2001).

The effects of personality on team performance have been widely studied over the past few decades based on a number of different measures, such as Jungian typology (Jung, 1921), Myers-Briggs Type Indicator (Myers & McCaulley, 1985), and Big-Five Personality Factors (Digman, 1990). While research on team composition has grown, there has been limited exploration of the effects of personality or cognitive diversity in design teams. This research attempts to fill this gap, particularly with respect to diversity of learning styles.

Learning styles broadly describe how people prefer to learn or their approach to learning. These are qualities that influence one's ability to "acquire information, to interact with peers and participate in learning experiences", (Grasha, 1996), and they affect academic achievement (Saracho, 1993). There are a variety of learning characterizations: Newland (1987) categorizes learners as common sense, dynamic, contemplative, and zealous; Leary (1957) classifies a person's behavior along two axes: dominant versus submissive and friendly versus critical; Felder (1988) examines learning using sensory versus intuitive, visual versus auditory, inductive versus deductive, and active versus reflective dimensions. David Kolb, the founder of experiential learning theory and of the learning styles explored with this research, describes learning as "the process whereby knowledge is created through the transformation of experience" and which follows a four stage cycle of learning (Kolb, 1984).

In his Experiential Learning Theory (Figure 1.1), Kolb posits that a person acquires knowledge by first grasping and then transforming experience. He defines these activities along two dialectically related continua: the Concrete Experience (CE) versus Abstract Conceptualization (AC) axis measures how an individual perceives information, and the Reflective Observation (RO) versus Active Experimentation (AE) axis measures how an individual processes information. These two continua intersect to create four quadrants, each representing a different learning style. Each individual's learning style is determined by which combination of learning modes he or she prefers for perceiving and processing information.

Kolb's experiential learning theory is particularly relevant to design and innovation because it neatly overlays models of design (Beckman & Barry, 2007). Designers must move fluidly between concrete and abstract worlds, and use both analysis and synthesis to create new designs. As they move through the design process, they begin with observations, then build frameworks, settle on a list of imperatives, and finally reach the design solution (Owen, 2007) (Figure 1.2). As such, Kolb's model is used over other learning style models for studying design teams. Figure 1.3 shows the design process and learning styles overlaid together.

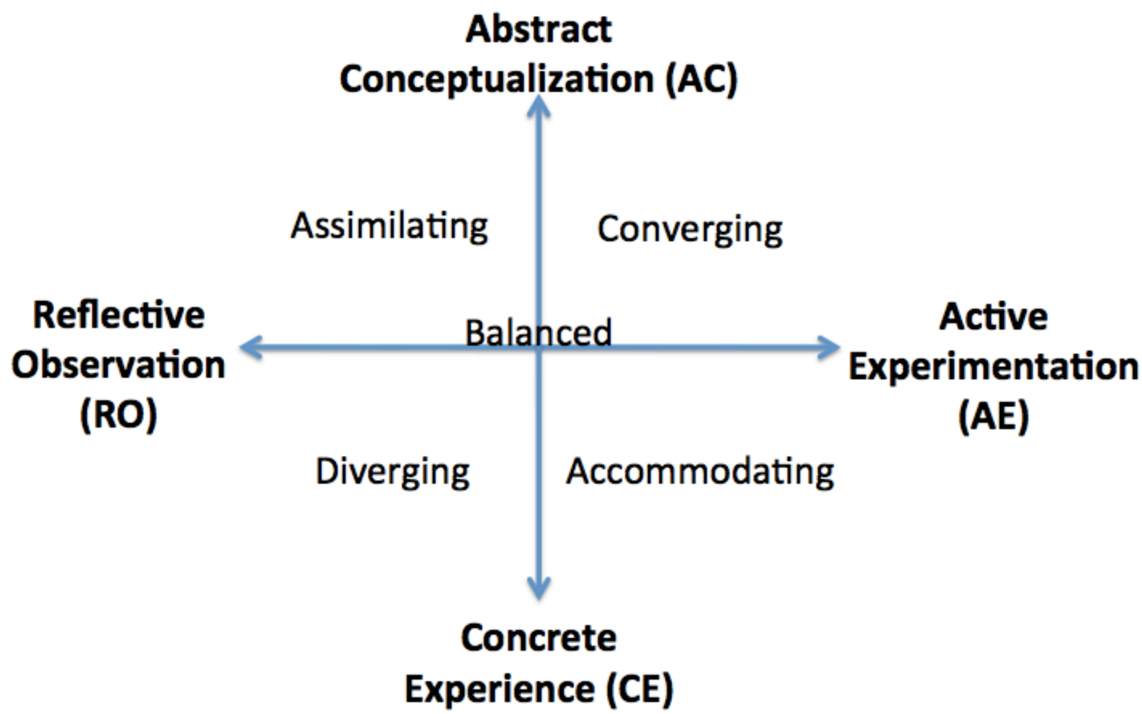

Figure 1.1: Kolb Learning Styles

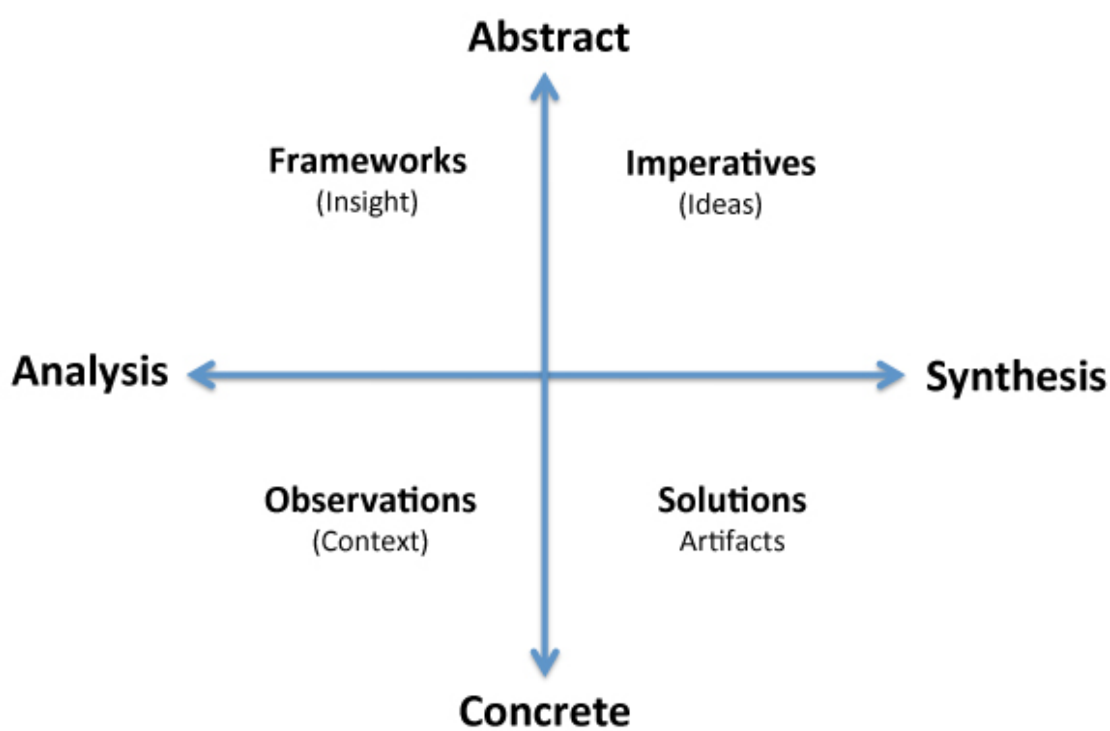

Figure 1.2: The Design Process

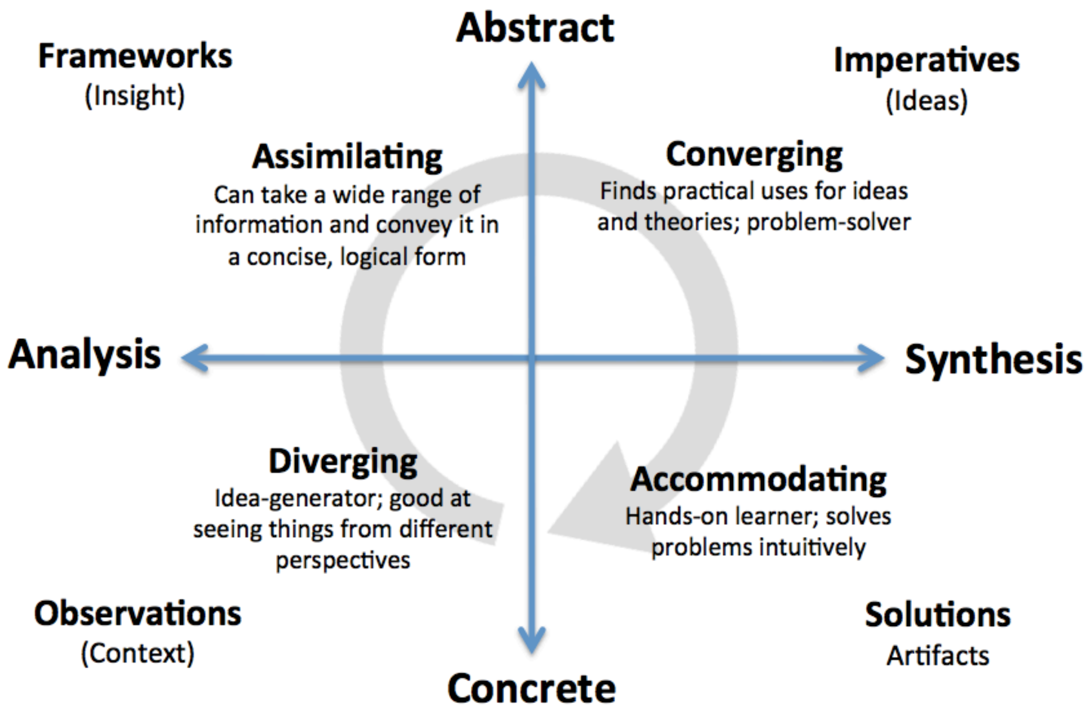

Figure 1.3: Design Process and Learning Styles

The four learning styles are Assimilating, Converging, Accommodating, and Diverging. Individuals may also be categorized as Balanced if their strengths lie along an axis rather than within a quadrant. The characteristics of each of the learning styles and the dimensions they emphasize are detailed below (Kolb, 1984).

Assimilating (Abstract Conceptualization and Reflective Observation)
People with an assimilating learning style excel at understanding a wide range of information and organizing it in a clear logical format. They always think before acting, prefer concise approaches, and need to have logical soundness to their theories. They value ideas and abstract concepts over people.

Converging (Abstract Conceptualization and Active Experimentation)
People with a converging learning style are problem-solvers. They enjoy thinking through ideas and then testing them out, to understand how something works. They prefer technical tasks and are best at finding practical uses for ideas and theories. They are less concerned with people and interpersonal issues. People with a converging learning style make decisions by finding solutions to questions and problems.

Accommodating (Concrete Experience and Active Experimentation)
People with an accommodating learning style are action-oriented and hands-on, and rely on intuition over logic. These people prefer a practical, experiential approach to learning. They are attracted to new challenges and experiences, and to carrying out plans. They commonly act on gut instinct rather than logical analysis. People with an accommodating learning style tend to rely on others for information rather than carrying out their own analysis.

Diverging (Concrete Experience and Reflective Observation)
People with a diverging learning style are able to look at things from different perspectives. They are sensitive and imaginative. They prefer to observe rather than do, and tend to gather information and use their imagination to solve problems. They are best at seeing concrete situations from several viewpoints, which makes them ideal candidates for idea generation.

Balanced (Abstract Conceptualization and Concrete Experience or Reflective Observation and Active Experimentation)
People with a balanced learning style have no strong preference for either extreme of the Processing or Perception continua combined. They are well-balanced learners.

There are extensive studies relating to learning styles, but research surrounding Kolb learning styles in design teams has not yet been fully explored. Learning styles are an important indication of how a person receives, processes, and shares information – all critical steps of the design process – and thus important to how a team performs in product development.

This exploration of design teams began with characterizing team diversity and an attempt to study the impact of team diversity on team performance. It started with different demographic factors: gender, disciplines, and ethnicity and then expanded to include cognitive diversity as well: personality, career experience, and learning styles. Ultimately, the focus shifted to studying how different learning styles within design teams might affect team outcomes based on the initial work of Beckman and Barry (2007), who framed the design cycle as requiring four distinct learning styles over the course of the design and innovation process.

As I launched this work, we discovered less diversity than initially expected. Fewer learning styles were present in the teams, and some styles were noticeably absent in the populations of people that might be expected to contribute them to design and innovation teams, such as product managers. Intrigued by this early finding, the focus of this shifted to completing a descriptive study of learning styles in the design population, both in the real-world and classroom settings. The research questions are:

- What is the makeup of Kolb learning styles in innovation-oriented populations?
    - Do the business, design, and engineering students that regularly participate on design teams in the academic word differ significantly in their learning styles?
    - Do people participating in design differ from the general population as Kolb documented it?
- What is the relationship between demographic diversity factors and learning styles?
- Does having a larger number of learning styles represented on a design team lead to greater team success?

In short, my research goal was to broaden the understanding of demographic and cognitive diversity in the design population, and assess the implications that follow for future design teams. The structure of this dissertation is as follows:

Chapter 2 provides a literature review on the topics relevant to diversity and teams and provides context for the research described in this dissertation. The chapter opens with a model for understanding the dynamics of diversity in teams derived from a review of the general literature on teaming and diversity. It then moves to reviewing the specific literature on learning styles and their connection to team dynamics.

Chapter 3 discusses the data sources and methodology used in this research. It provides a description of the research test bed used in this research and the process used to collect the data.

Chapter 4 explores the characterizations of the design population. This chapter compares and contrasts learning styles across a variety of populations that are engaged in design and innovation work including: differences between college students and professionals in design, engineering, and business; differences among genders; differences by ethnic group; differences across disciplines; and differences by country. The first section of the chapter characterizes the student population. The second section examines the industry population. The third section compares student and industry populations and reviews the entire database as one.

Chapter 5 presents findings on learning style differences between international and domestic students. The confidence levels in ABET skills and Kolb learning style preferences in lower division students in project-based design courses offered at the University of California at Berkeley and the Korea Advanced Institute of Science and Technology are presented. The confidence levels in ABET-related engineering and design skills are compared by country and gender, as well as learning styles.

Chapter 6 describes a study on how design teams performed with respect to the mix of learning styles among team members. Now that diversity within the populations has been characterized, this chapter culminates with the examination of the role of diversity in design team performance. It provides a discussion of diversity factors that affect the dynamics and success of a design team, and how these factors may be leveraged in design practice. The chapter also considers other demographic factors, such as discipline and gender.

Chapter 7 concludes this dissertation and provides directions for future research.

Chapter 2

Literature Review

This chapter provides a literature review on the topics relevant to diversity and teams and provides context for the research described in this dissertation. The chapter opens with a model for understanding the dynamics of diversity in teams derived from a review of the general literature on teaming and diversity. It then moves to reviewing the specific literature on learning styles[2] and their connection to team dynamics.

2.1 Framing the Literature

The literature defines teams along a broad spectrum. On one end of the spectrum lie “groups”, which are defined as collections of individuals who perform discrete functions in a coordinated manner (Bereiter & Scardamalia, 1993). On the other end of the spectrum lie “teams”, which are defined as more cohesive units of interdependent people working together towards a shared goal (Katzenbach & Smith, 1993) (Rothwell, 2004). Amy Edmondson (2012) develops this definition further, by describing the central role that teams play in organizations and introducing teaming as a verb rather than just a noun. She describes teaming in organizations as the “engine of organizational learning… a way of working that brings people together to generate new ideas, find answers and solve problems.” Importantly, she points out that “people have to learn to team; it doesn’t come naturally.”

Researchers have been studying diversity of team members for decades. Sethi (2000) examined the role of superordinate identity in a team and how it affects the final product’s performance, finding that superordinate identity indeed enhances the performance of the new product developed by a team. Froehle (2000) looked at the impact of team-based organizational structure on the process for new service development, and found no direct relationship between the two. Hitt (1999) found that organizational context in teams, specifically the presence of top management support, has more influence on team success than internal team characteristics.

This research focuses on teams and teaming, and on the role that diversity plays in both the satisfaction that team members experience as well as the performance outcomes of the team. A review of the literature on diversity and design teams reveals a shared model of how diversity affects both. Over thirty papers studying the effects of diversity on team performance were reviewed. All of the research papers were interested in some measure of diversity, whether gender, functional background, ethnicity, or others. From there, the research varied widely. Some papers examined the direct effects of diversity on teams, such as increased conflict. Other papers

[2] “Learning styles” will henceforth refer to learning styles as defined by David Kolb’s model and described above in Chapter 1.

studied the effects of diversity on team outcomes, ignoring the intermediary variables. And yet others focused on the ways in which teams might leverage or mediate the effects of diversity. Thus, the model in Figure 2.1 was constructed suggesting first that there are many different measures of diversity, that diversity has some immediate effects on teams (e.g., increases conflict), that there are mechanisms to either leverage or cope with those effects (e.g., co-locating the team) and finally that there are a large number of potential outcomes that might be measured both internal (e.g., team member satisfaction) and external (e.g., team performance against designated metrics) to the team.

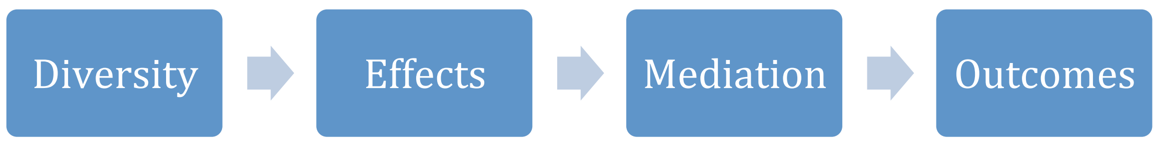

Figure 2.1: Diversity in Design Teams Model

The following sections define each of these categories of variables, and include lists of the variables identified in this literature review.

2.1.1 Diversity

Diversity is commonly defined as: a range of different things or having a variety of forms, types, ideas, etc. In the context of a team, it is defined as the "distribution of differences among the members of a unit with respect to a common attribute" (Harrison & Klein, 2007). The "common attribute" might have to do with cognitive diversity or "highly job related" characteristics such as field of study and education or it might refer to demographic diversity or "less job related" attributes such as gender, age, and ethnicity (Jackson et. al, 2003) (Jehn et. al, 1999).

The most common diversity factors investigated are gender, ethnicity, age, organization and team tenure, education level, college discipline, and functional background. Within the context of the literature reviewed here, diversity factors explored to date include (see Table 2.1 for the specific references):

- D1. Functional backgrounds
- D2. Demographic variables (age, gender, race)
- D3. Team tenure
- D4. Routines or working styles of team members
- D5. Knowledge sharing skills
- D6. Attitudes, beliefs, and values
- D7. Personality differences

Each of these factors can be fairly readily defined and the members of a team can be identified by those factors. The question then becomes how to actually put a metric around the diversity in any given factor that is present on the team. There are three constructs that help do so: separation, variety, and disparity (Harrison & Klein, 2007).

Separation

Separation refers to whether an individual does or does not have a specific attribute, or holds or does not hold a specific position. It is defined as the composition of differences in opinion, attitude, or similar characteristics. For example, separation may be determined by whether team members agree or disagree on the team mission. Reduced separation results in more successful teamwork.

Variety

Variety refers to the number of diverse qualities in a team. It is defined as the composition of differences in kind, source, or category of relevant knowledge or experience. For example, a team has minimum variety if all team members have the same functional background. Teams with moderate variety may fall victim to under-sharing relevant information because they believe other members already have similar knowledge, thus decreasing their success. A team with maximum variety is generally more successful than a homogeneous team, so long as the attributes match the task. A team solving a relatively simple problem (e.g., how to pull an arrow out of a target) does not benefit as much from variety as a team that is working on a more difficult problem (e.g., how to rid the world of slums).

Disparity

Disparity refers to the quantity, value, or level of each diverse factor. It is defined as the composition of differences in proportion of assets or resources. For example, a team with minimum disparity might be made up of individuals that are all at an identical income level. Disparity is considered high if only 10% of the team holds the shared attribute and it is considered low if 90% of the team holds the shared attribute. High disparity may breed competition and foster conformity.

2.1.2 Effects

The existence of diversity, of any sort, on a team has potential for immediate negative consequences. For example, diversity raises conflict and decreases unity (Milliken & Martins, 1996). Negative results in the form of team conflict and less communication have been documented (Brown & Eisenhardt, 1995). In an argument against the age-old adage "opposites attract", Byrne (1971) suggests that "similars attract" and that homogeneous teams cooperate and collaborate better than diverse teams. This is further supported by Brewer's (1979) intergroup bias theory that team members with similar attributes will band together in small groups, thus lowering productivity of the larger group. Williams and O'Reilly (1998) also found that diversity in a team diminishes morale and group cohesion and fosters conflict. It is understood that individuals behave differently in group settings than when they are alone (Barton Jr., 1926) (Beaty & Shaw, 1965).

The review of this literature suggests that not all of the immediate effects of diversity in a team are negative. The effects identified in the papers reviewed are categorized: (1) positive effects were those that improved the collaborative environment, (2) negative effects were those that increased conflict, and (3) neutral effects were those that did not have a bias in either direction. All of the effects listed below are linked to the papers from which they are drawn in Table 2.2.

Positive Effects [Collaborative]

E1. Trust in team members, identity
E2. Creative behavior
E3. Collaborative communication
E4. Citizenship behavior
E5. Shared mental models
E6. Partition and division of tasks

Negative Effects [Conflicting]

E7. Creative abrasion
E8. Contentious communication
E9. Intra-team task disagreement
E10. Individual differences

Neutral

E11. Centrality-focal point of leadership
E12. Social cohesion

2.1.3 Mediation

Researchers had previously conformed to an "input-process-outcome" framework in their research on diversity. But these consistently mixed results spawned an exploration into "why" and culminated with an understanding of mediating and moderating factors. When Ancona and Caldwell (1992) performed their study on the homogeneity of organizational tenure and functional diversity in 45 design teams, they found, yet again, that functional diversity could have both positive and negative effects on team performance. They further interpreted these results to show positive effects on external communications and negative effects on teamwork and internal conflict. This study helped establish the model of intermediary variables affecting final outcomes. Joshi and Roh (2009) similarly adjusted their study from evaluating the effect of diversity factors directly on team performance to one of understanding contextual factors affecting the relationship between diversity and performance. In effect, they sought to understand the "black box" between demography and performance. Lawrence (1997) similarly observed that there are intervening factors between diversity and outcomes that should be studied.

The mediating variables that are uncovered in the literature are listed below. These variables are once again connected in Table 2.2 with the papers that identified them.

M1. Rewards
M2. Leadership and top management support
M3. Physical proximity
M4. Supplier and consumer involvement
M5. Organizational politics

M6. Decision making strategy
M7. Communication with boundary groups
M8. IT technology integration
M9. Encouragement to take risks
M10. Synergistic communication and formation of group identity
M11. External information and communication (Gatekeepers)
M12. International development
M13. Diversity orientation and HR policies
M14. Task complexity
M15. Support networks employed by the Company

2.1.4 Outcomes

A frequent assumption is that teams with more diversity will be more successful because of the wider range of inputs that might be made to the team's effort. Some studies indeed show that individuals are more successful and exhibit better problem-solving skills when they participate as a team (Barton Jr., 1926) (Watson, 1928) and that cross-functional design teams exhibit greater creativity and innovation (Bell et. al, 2011). Keller (2001) found that technical quality and schedule and budget performance improved with a functionally diverse team. Cross-functional teams also resulted in more high quality products, faster development times, and happier team members (Brown & Eisenhardt, 1995). Not all studies of diversity in teams, however, come to the same conclusion.

Ultimately, outcomes are defined within the confines of the teams and of the nature of the work those teams are doing. Some of the research focuses more on internal team metrics, while other studies examine the more external effects or the outputs of the teams. Here are the outcome metrics uncovered in the literature review:

Internal Metrics

O1. Team performance
O2. Team adaptability to change
O3. Constraint adherence
O4. Personal affect and how it relates to performance
O5. Innovative behavior and creativity
O6. Social network patterns
O7. Helping behavior
O8. Information use
O9. Social integration and successful team establishment

External Metrics

O10. Effectiveness: how much product meets targeted need
O11. Efficiency: time to produce output
O12. Quantity of new ideas introduced
O13. New product performance and quality
O14. Goal achievement

O15. Competitive advantage and profit
O16. Financial performance
O17. Quality of performance

Tables 2.1 and 2.2 below summarize all of the papers reviewed and the variables each paper examined.

Table 2.1 lists each paper reviewed with the year it was published, the sample size of its study, and the diversity measures that were evaluated. The majority of the studies examined the diversity of functional backgrounds (D1), yet only one paper explored a team's attitudes, beliefs, and values (D7). Two studies look at personality differences (D8), but neither examined learning styles, the topic of this dissertation.

Table 2.2 lists which effects, mediating factors, and outcomes were explored. The individual factors are represented by the labels listed in the introductory sections above, e.g., E1 represents "trust in team members", M1 represents "rewards", O1 represents "effectiveness", and so on. It is interesting to note that some factors received much more attention than others, which may imply greater influence or perceived influence on team outcomes. Likewise, some studies did not evaluate all four factors, thus potentially disregarding certain diversity impacts on the team. These are denoted by "---".

Table 2.1: Papers by Year, Sample Size, and Diversity Measures [Legend below]

Authors	**Year**	**Sample Size**	**Diversity Measures (D1-D7)**
Ancona and Caldwell	1992	45 teams	D1, D2, D3
Bowers, Pharmer, and Salas	2000	567 teams	D1, D4, D2,
Cady and Valentine	1999	50 teams	D1, D2
Callaghan	2009	9 teams	D1, D7
Cohen and Bailey	1997	1265 teams	D3
Deeter-Schmelz, Kennedy, and Ramsey	2002	85 teams	D2
Devine et al	1999	128 subjects	D1, D2
Fisher, Maltz, and Jaworksi	1997	180 subjects	D1
Froehle, Roth, Chase, and Voss	2000	175 firms	D1
Gebert, Boerner, and Kearney	2010		D1
Madhavan and Grover	1998	5 teams	D1, D4, D5
Hitt et al	1999	16 team members	D1
Horwitz and Horwitz	2007	37 studies	D1, D2

Howell and Shea	2006	269 subjects	D2
Janssen and Huang	2008	157 team members	D1, D2, D3
Keller	2001	93 teams	D1, D3
Lin et al	2005	45 teams	D1, D4
Lovelace, Shapiro, and Weingart	2001	328 teams	D1
McGrath, MacMillan, and Venkataraman	1995	160 subjects	D3
Mohammed	2001		D1, D7
Peelle	2006	6 teams	D1
Sethi, Smith, and Park	2001	141 teams	D1
Sethi	2000	118 teams	D1, D3
Shoobridge	2006	97 studies	D2
Tyran and Gibson	2008	57 teams	D1, D2, D6
Valenti and Rockett	2008	49 subjects	D3, D2
Van der Vegt and Van der Vliert	2005	20 teams	D1
Van der Vegt and Janssen	2003	41 teams	D1, D2

Legend: D1 (functional background), D2 (demographic variables), D3 (team tenure), D4 (working styles of team members), D5 (team size), D6 (knowledge sharing skills), D7 (attitudes, beliefs and values), D8 (personality differences), D9 (type of team)

Table 2.2: Papers by Effects of Diversity, Mediating Factors, and Outcome Measures [Legend below]

Authors	**Effects of Diversity (E1-E12)**	**Mediating Factors (M1-M15)**	**Outcome Measures (O1-O17)**
Ancona and Caldwell	E3, E8	M7	O1
Ancona	E4	---	---
Bowers, Pharmer, and Salas	---	M14	O1, O9, O12, O17
Brown and Eisenhardt	E3, E8	M2, M4, M5, M10, M11	O10, O11, O16
Cady and Valentine	E1	---	O12, O13
Callaghan	---	M2, M5	O12, O13

Cohen and Bailey	E7, E8, E9, E11	M1, M2	O9, O10, O11
Deeter-Schmelz, Kennedy, and Ramsey	E14	M2, M3	O1, O14
Devine et al	E1, E9, E11	M2, M6	O3, O10, O11
Fisher, Maltz, and Jaworksi	E3, E5	M1, M2, M7	O6, O8
Froehle, Roth, Chase, and Voss	---	M2, M5, M6, M8	O4, O10, O11
Gebert, Boerner, and Kearney	E3, E5, E8, E9, E10	M5, M10	O1, O3, O13
Madhavan and Grover	E1, E5, E7	---	O10, O11
Hitt et al	E3, E5	M2, M3, M4, M5	O1, O10
Horwitz	---	---	O10, O11
Horwitz and Horwitz	---	---	O9, O12, O17
Howell and Shea	E11	M2, M5, M7	O1
Janssen and Huang	E1, E2, E4, E10	---	O1
Keller	E1, E3, E4, E9, E10	---	O3, O10, O13
Lin et al	E1, E6, E11	---	O1
Lovelace, Shapiro, and Weingart	E1, E3, E8, E9	M2	O1, O2, O3, O12,
McGrath, MacMillan, and Venkataraman	E3, E5	M2	O14, O15
Mohammed	E5, E11	M6	---
Peelle	E3, E5	M2, M6	O10
Sethi, Smith, and Park	E2, E3, E7, E8, E11, E12	M2, M4, M9	O5, O10
Sethi	E1	M3	O13
Shoobridge	---	M32 M12, M13, M15	O2
Tyran and Gibson	E3, E5	---	O1
Valenti and Rockett	E10	---	O6
Van der Vegt and Van der Vliert	E9	M6	O7
Van der Vegt and Janssen	E1	---	O5
Weick and Roberts	E3, E5	---	O1

Legend
E1 (trust in team members), E2 (creative behavior), E3 (collaborative communication), E4 (citizenship behavior), E5 (shared mental models), E6 (partition and division of tasks), E7 (creative abrasion), E8 (contentious

communication), E9 (intra-team task disagreement), E10 (individual differences), E11 (centrality-focal point of leadership), E12 (social cohesion)

M1 (rewards), M2 (leadership support), M3 (physical proximity), M4 (supplier and consumer involvement), M5 (organizational politics), M6 (decision making strategy), M7 (communication with boundary groups), M8 (IT technology integration), M9 (encouragement to take risks), M10 (synergistic communication and formation of group identity), M11 (gatekeepers), M12 (international development), M13 (diversity orientation and HR policies), M14 (task complexity), M15 (support networks)

O1 (team performance), O2 (team adaptability), O3 (constraint adherence), O4 (personal affect), O5 (innovative behavior), O6 (social network patterns), O7 (helping behavior), O8 (information use), O9 (social integration), O10 (effectiveness), O11 (efficiency), O12 (quantity of new ideas), O13 (new product performance), O14 (goal achievement), O15 (competitive advantage and profit), O16 (financial performance), O17 (quality of performance)

It would have been interesting to perform a meta-analysis that included all of these variables, and to extract some more general conclusions that cut across the literature. Unfortunately, the diversity in the metrics used across the papers was too large, and the number that reported useful statistical data was not sufficient to create a conclusive analysis. A number of papers reported conflicting results, but often used different combinations of metrics, making comparison of their results difficult. We are thus left with the need for more comprehensive research on diversity and teams that includes more of the relevant variables and thus allows us to test the broader model that is presented here.

2.2 Literature on Learning Styles

As the research on team diversity grows, focus has expanded to product design teams. Because design teams are intentionally created with different skillsets and experiences, they are inherently diverse and naturally interdependent, and thus ideal candidates for observing the effect of diversity. Design teams also provide an excellent platform for studying team dynamics because of the close team member interactions. Tuckman and Lorge (1962) found that a group's problem-solving success is more dependent on having a capable team member than on having a functional group. It follows that the learning style of each team member might have an effect on group interactions.

2.2.1 The Importance of Learning Styles

Learning styles have been largely studied in education, with interesting implications from mismatched learning styles that can translate to design team interactions. Pask (1988) finds that students learn better when lessons are delivered in their preferred style, resulting in better information retention, attitudes toward learning, and overall effort and effectiveness (Dunn et. al, 1981) (Rasmussen, 1998). Felder and Silverman (1988) explore learning styles in engineering education and find negative impacts from mismatched learning styles between professors and students. Conversely, they argue that students are more satisfied and develop better mental agility to adapt and succeed when forced to adjust to a teaching style different from their preferred style (1988).

There are also a variety of studies within specific disciplinary fields that describe how learning styles apply to those fields. In education, learning styles were matched with teaching skills, and considered as a framework for curriculum and program design (Fox & Bartholomae, 1999). In business, learning styles were matched with management style, decision-making, and problem solving skills (Loo, 2002). In computer and information science, learning styles were compared against online learning behaviors and performance in computer training (Lu et. al, 2007). Some researchers also examined learning style trends of surgery residents and nurses in the medical field (Engels & de Gara, 2010).

These research studies demonstrate that learning styles matter in how people react and adapt to different situations, yet the effect of learning styles within design teams is mostly unexplored. This provides the important opportunity that I have leveraged in this research.

2.2.2 Learning Styles in General Population

In a 1981 study, Kolb sampled a large population of practicing managers and graduate students in management. From this emerged a pattern of relationships between learning styles and undergraduate majors that seemed to indicate that undergraduate discipline is an important influence in learning style. The academic disciplines could be separated into four fundamental groups that fit into the learning style quadrants.

Kolb also posits that some learning styles will be typical in certain vocations, because of the experiences one undertakes in studying a specific profession (Kolb, 1984) (Loo, 2002). For instance, Kolb found that individuals in human-related professions (educators, social workers, nursing) tended towards concrete learning and were more likely to be accommodators. Engineers and decision-makers were high in converging learning styles, whereas professionals in the arts and humanities were high in diverging learning style. Mathematicians and scientists mostly preferred the assimilating learning style (Kolb, 2005).

Table 2.3: Learning Style Characterizations

	Accommodating	**Converging**	**Assimilating**	**Diverging**
MBTI	Extraverted, Sensing	Extraverted, Thinking	Introverted, Intuitive	Introverted, Feeling
Undergraduate Disciplines	Business and management	Physical sciences and engineering	Natural sciences and math	Humanities and social sciences
Professional Field	Business and organizational field	Technology and environment science	Sciences, information, or research	Social service, arts, and communication
Job Role	Task accomplishment and decision making	Technical and problem solving	Data gathering and analysis	Establishing relationships, effective communication
Adaptive Competencies	Acting skills	Decision skills	Thinking skills	Valuing skills

There has also been extensive research that correlates learning styles with various demographic factors, such as personality, culture, professional career, job role, and adaptive competency. Table 2.3 summarizes general characterizations of learning styles across some of the factors that were examined by Kolb (1981).

Design teams are generally composed of members from across the functional areas of a firm, including business and engineering. Thus, one might imagine that the preponderance of participants on those teams would display accommodating and converging learning styles. Similarly, as design and innovation projects in the classroom draw from students in multiple disciplines, one might expect to see even more representation of different learning styles. However, as revealed in this literature review, there is a lack of exploration of diversity in design teams, especially in the context of learning styles despite the logical overlay of learning styles with the design process.

This research shows the extent to which the learning styles are represented in design and innovation activities, both in industry and in the academic world. It examines learning styles within a design population to provide an understanding of learning styles in innovation-oriented populations and explores how designers compare against the general populace, and ultimately helps leverage diversity to optimize design outcomes.

Chapter 3

The Database

This section contains a summary of the test bed used in this research and the process used to collect the data.

3.1 Research Test Bed

The primary goals of this research are to understand the diversity in the design population from a learning style perspective, and then to understand the effects of diversity in learning styles on design team outcomes. To that end, diversity information was gathered from people engaged in a variety of innovation- and design-oriented activities to build a relevant database. Below are the major groups that were surveyed:

Academic
Business Administration (BA) Students at UC Berkeley
Students enrolled in four different BA programs at UC Berkeley, including full-time MBA students, evening-weekend MBA students, executive MBA students, and undergraduate BA students.

Design Project Students at Various Universities
Students enrolled in various project-based design courses at UC Berkeley, Stanford University, University of Pennsylvania, and Korea Advanced Institute of Science and Technology. Each course focused on teaching the innovation process and was made up of multi-disciplinary students, with a mixture of engineering, business, design, and art majors. Data were also gathered from students enrolled in an undergraduate Integrated Design Program at an anonymous U.S. university who represented engineering, business, and design disciplines.

Corporate
Consultants in an International Corporation
This group comprises a large consultancy population that was learning about the design process to integrate into their company's process.

Product Managers
These product managers were participants in a UC Berkeley-hosted program that teaches design thinking and managing innovations, with emphasis on balancing the dual roles of General Manager and Product Designer through the design cycle.

Executives and Academic Administrators
This group is made up of company executives from a variety of fields (e.g., information technology, banking, consumer products, biotechnology, medicine) and academic administrators who were interested in innovation and were participants in leadership development and innovation programs at UC Berkeley.

3.2 Data Collection

The data were collected through online surveys administered to each participant. The list below describes the specific diversity information that was captured:

Learning styles, based on David Kolb's Experiential Learning Theory and defined as Assimilating, Converging, Accommodating, Diverging, and Balanced. The Learning Style Inventory used to identify the learning styles is described in more detail below.

Gender, defined as male and female.

Undergraduate disciplines, organized into the following eight categories: Accounting, Applied and Fine Arts, Business, Computer Science, Engineering, Science and Math, Social Science, and Undeclared.

Ethnicity, organized into the following seven categories: Asian, Australian, Black or African American, Caucasian or White, Hispanic or Latino, Mixed Race, and Other.

Job title, captured in freeform response and then organized between Executives (those who manage others and have decision-making authority) and Individual Contributors (non-management members with day-to-day responsibilities).

Myers Briggs Type Indicator (MBTI) type, which identifies personality type based on preferences over four dichotomies: intuition versus sensing, feeling versus thinking, perception versus judging, and introversion versus extraversion. The personality assessment tool[3] defines sixteen different MBTI types.

For students engaged in project-based design courses, the information below was also collected.

Team and 360 evaluations, in which students evaluated the performance of each individual on their team as well as their team's overall performance. These data were captured through comprehensive surveys administered at the halfway point and end point of the project and provided valuable insights into actual interactions between team members. This ultimately helped paint a clearer picture of how teams of different makeups react and adapt to one another.

Assessment of ABET skills, in which students self-assessed their strengths in design and engineering skills defined by Accreditation Board for Engineering and Technology. These responses were captured to investigate how design students from different backgrounds perceive their own skills differently, and possibly participate in design teams differently.
Table 3.1 enumerates the responses that were captured for each group in these categories. The totals for each column are different because not all diversity factors were recorded across the entire population.

---

[3] The Humanmetrics Jung Typology Test instrument at www.humanmetrics.com was used as a proxy for identifying MBTI personality types.

Table 3.1: Summary of Data Collected

	Learning Style	Gender	UG Major	Ethnicity	Job Level	Company	MBTI type
Academic	4616	4616	3467	2085	1950	1836	1138
Corporate	2070	2070	374	785	1503	1732	0
Grand Total	**6686**	**6686**	**3841**	**2870**	**3453**	**3568**	**1138**

Learning Style Inventory

There are currently six versions of the Learning Style Inventory (LSI) in circulation. The LSI is a validated and reliable tool and is widely used in research and education [XXXX]. Version 3.1 was published in 2005 and is used in this research with permission from the Hay Group.

The learning style inventory is made up of 12 questions. Each question prompt gives four different sentence endings that the respondent must rank in order of preference. The tool is worded such that each sentence ending correlates to a different dimension of learning (e.g., Concrete Experience, Abstract Conceptualization, Active Experimentation, and Reflective Observation), thus requiring respondents to purposefully rank the four different learning modes as they answer each question.

These rankings are then evaluated collectively across all 12 questions to calculate each person's score in the four learning orientations (abstract, concrete, active, and reflective). A higher score represents a higher preference for that learning mode and these scores are used to identify overall learning styles.

3.3 High Level Summary of Data

The entire population is made up of 34.3% females and 65.7% males and can be divided into college students (24.8%), graduate students (44.2%), and working professionals (31.0%). Below is a visual of the learning style makeup of the population (Figure 3.1).

The large representation of converging learners (39%) and small representation (3%) of diverging learners in the population is a very startling result. The absence of diverging learners is particularly concerning because of the contributions they bring to the design cycle. People with diverging learning style are good at seeing situations from multiple viewpoints, at understanding people, and at recognizing problems. With rising interest in customer-focused design, it is important that design teams are able to listen with an open mind and can imagine the implications of ambiguous situations; the low numbers of divergers in the population means their skills are lacking from the process.

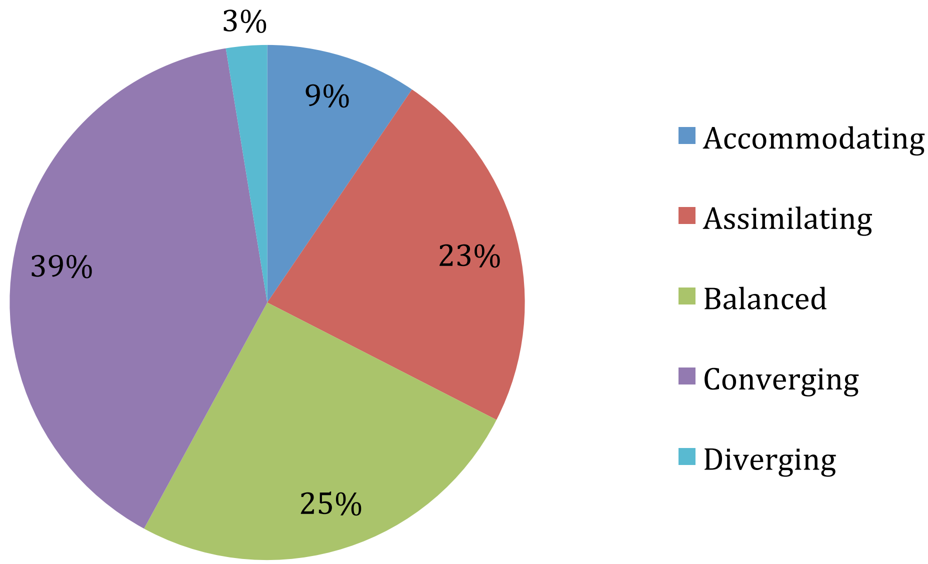

Figure 3.1: Overall Population Learning Styles

Table 3.2: Learning Style Scores for Overall Population

	AC	AE	CE	RO
Mean	34.29	32.62	24.87	28.12
Std Dev	6.92	6.68	5.97	7.06

The dominance of convergers has similar implications. Converging learners are generally strongest at problem solving and decision-making, but are not as well suited for framing problems. This is troublesome if the problems that convergers are being asked to solve are unclear or ambiguous. They can only find effective applications for ideas and theories if they understand what they are trying to solve. Otherwise, they may find themselves in an endless cycle of ideas.

Table 3.2 shows the overall learning style scores of the entire population, which further support the converging learning style profile. The lowest score is in the Concrete Experience dimension [24.87], whereas the highest score is in the Abstract Conceptualization dimension [34.29]. In general, this is a population of abstract thinkers.

These findings set up the discussion and analysis to presented in the following chapters. The population will be further characterized against other diversity factors and evaluated in detail, and the results provide further insight into this innovation-oriented group.

Chapter 4

Overall Learning Style Characterizations

This chapter compares and contrasts learning styles across a variety of populations that are engaged in design and innovation work including: differences between college students and professionals in design, engineering, and business; differences among genders; differences by ethnic group; differences across disciplines; and differences by country. The chapter is separated into three sections. The first section characterizes the student population. The second section examines the industry population. The third section compares student and industry populations and reviews the entire database as one. In sum, this chapter addresses the first and second research questions posed in Chapter 1.

4.1 Students

In this section, the learning styles of business, design, and engineering students participating in design teams are examined. This group offers a key look into the learning style preferences of academics in an innovation-oriented population and is interesting for a variety of reasons. First, these students will ultimately enter the professional workforce, with design-oriented thinking, if not directly into the design world. Do their preferences reflect those of the professional design population, the general population, or are they of their own makeup? These students are also definitively split into specific majors, but participating in design activities. What prevails in their learning style preferences – design thinking or major fields? The same question can be raised about influence of gender bias. This analysis will provide a characterization of the academic part of the design population.

4.1.1 Survey Populations and Methods

These data were gathered from 2010 through 2012 from a number of different student populations at the undergraduate and graduate level (Table 4.1). The main disciplines represented in this pool are engineering and business administration, but include data from other fields within the sciences and humanities as well.

The undergraduate student data were collected at three universities:

1. Korea Advanced Institute of Science and Technology (KAIST): from students taking a freshman-level course focused on the fundamentals of conceptual design and critical thinking.
2. Anonymous U.S. University: from the entire entering class of 2015 to a new Integrated Design Program (IDP).
3. University of California, Berkeley (UCB): from students enrolled in an upper-level course focused on the engineering design process and conceptual design of products.

Table 4.1 Overall Survey Population[4]

	# of Participants
Undergraduate	828
Graduate	1397
TOTAL	2225

The graduate student data were collected primarily through various classes on design-related topics offered at the UCB Haas School of Business, the UCB College of Engineering, and the California College of the Arts.

The data were collected through online surveys that were administered at the beginning of the classes. Information was collected about learning styles, as well as demographic data about gender, ethnicity, and undergraduate major.

4.1.2 Results

4.1.2.1 Comparison of Learning Styles By Gender

First, the four learning styles are evaluated to determine whether there is equal representation across genders. Table 4.2 shows the distribution of learning styles by gender. Pearson's Chi-Squared Test for categorical data was used and results show that there are populations in which the learning styles of males and females differ, but this does not hold true for all populations, most notably the engineering population.

Table 4.3 summarizes the p-values for the significance of gender differences in each of the target populations in the study. This analysis is based on the percentages of learning styles present in the population. There is statistical significance ($p \leq 0.05$) in six instances, suggesting that learning styles are different by gender in certain circumstances. Overall, there is a statistically significant difference in learning styles between females and males at aggregate levels, such as in the entire population of subjects.

When the overall population is broken down, not all groups show statistically significant differences by gender. Collectively, the population of all graduate students (with a p-value of 0.00), the population of all MBA students (again with a p-value of 0.00), the population of all undergraduate students (with a p-value of 0.01), and all undergraduate business students (p-value of 0.02) show significant differences by gender. The graduate engineering students (p-value = 0.29) and undergraduate engineering students (p-value = 0.20) as well as the KAIST students, who are largely engineering, (p-value = 0.49), do not show any statistically significant gender-related learning style differences.

[4] Section 4.1 only covers data captured from 2010 to 2012; the additional data described in Chapter 3 was not included in this section analysis.

Table 4.2 Distribution of Learning Styles in the Study Population (2010-2012)

	Study Population				
	Female		Male		Total
Accommodating	120	16%	127	9%	247
Assimilating	128	17%	340	23%	468
Balanced	204	27%	273	19%	477
Converging	265	35%	700	47%	965
Diverging	38	5%	30	2%	68
Grand Total	**755**		**1470**		**2225**

Table 4.3 Statistical Significance of Gender Differences in Each Study Population

	Gender	**Total**	**p-value**
1	Entire population	2225	**0.00**
2	Graduates (All)	1431	**0.00**
3	Graduates (Engineering)	113	0.29
4	Graduates (MBA)	1275	**0.00**
5	Undergraduates (All)	828	**0.01**
6	Undergraduates (KAIST)	400	0.49
7	Undergraduates (Business Administration)	85	**0.02**
8	Undergraduates (Engineering)	150	0.20
9	Undergraduates (IDP)	179	**0.03**

Table 4.4 Distribution of Learning Styles in Undergraduate Students
by Institution and Major

	IDP		**UCB - Business Administration**		**UCB - Engineering**		**KAIST**	
	Female	Male	Female	Male	Female	Male	Female	Male
Accommodating	24%	16%	4%	21%	13%	5%	11%	13%
Assimilating	13%	20%	13%	14%	25%	22%	16%	23%
Balanced	49%	38%	34%	14%	26%	26%	35%	33%
Converging	11%	27%	43%	50%	38%	45%	32%	27%
Diverging	2%	0%	4%	0%	0%	1%	7%	4%
Grand Total	**123**	**56**	**23**	**14**	**16**	**76**	**133**	**273**

By contrast, the learning styles of the non-engineering populations – UCB Business Administration and the IDP at a small, private university focused on Liberal Arts – do show statistically significant differences in learning styles between genders. That being said, the breakdown of the MBA population reveals 25% come from an engineering background and 15% come from a computer science, science, or math background. This means 40% of the MBA group formerly practiced in engineering or related areas before transitioning into the business field. This reveals an intriguing pattern of current engineering students having no significant gender differences in Kolb learning styles. These gender neutral results from the engineering student population could be due to a bias in self-selection or in socialization in technical majors.

4.1.2.2 Comparison of Learning Styles by Status, Discipline, and Location

There are several other factors besides gender that distinguish the populations studied, including status, discipline, and geographical location. In this section, the outcome of comparisons of learning styles across these dimensions is described. The results of comparisons across academic institutions for the undergraduate students are summarized in Table 4.5 and p-values below 0.05 signify statistically significant results. In this table, "U.S. Universities" represents aggregate data from UCB, CCA and IDP (Table 4.5, Item 1). Table 4.6 then displays the learning style distribution of these undergraduate populations.

The results for the Korean university students are most striking (Rows 1-5 in Table 4.5), as they show statistically significant differences with all of the other student populations studied except for the CCA students. Although it is not surprising that these technically-oriented students would show up as different than the design-oriented IDP students, it is surprising that they showed up differently than the UCB undergraduate engineering population. It could be that there are other factors at work, such as age (the population at KAIST consisted of Freshman/Sophomores, while the population at UCB was composed of Junior/Seniors) or cultural differences between the Korean education system and the U.S. one.

The only student population that KAIST is not statistically different from is that of the California College of the Arts (CCA) students. In fact, CCA students are not statistically different from any other population. This is surprising, considering the CCA students specialize in Art and Design, which are inherently different from the technical concentrations of the other undergraduate populations we surveyed. However, the lack of significance could very well be due to the small numbers of students from CCA that were part of this study population, making them statistically indistinguishable. The results from KAIST and UCB (Engineering) students are different than the population at IDP, suggesting that there is a difference in learning styles between engineering-focused students and design-focused ones.

Alternatively, there is a high statistical difference between the IDP students and the UCB Engineering students (p-value = 0.00), which may highlight a difference between technical and non-technical disciplines. This difference in learning styles is predicted by previous research linking disciplines with learning style preferences (Table 2.3). However, the actual learning styles predicted for each field do not match those of our population, with the exception of engineers as converging learners.

Table 4.5 Statistical Significance of Learning Style Differences between Undergraduate Populations by Institution and Major

	Undergraduate Students	p-value
1	KAIST vs. U.S. Universities	**0.00**
a	KAIST vs. *IDP*	**0.00**
b	KAIST vs. **UCB** (Engineering)	**0.00**
c	KAIST vs. **UCB** (Business Admin)	**0.02**
d	KAIST vs. CCA	0.72
6	CCA vs. **UCB** (Engineering)	0.41
7	CCA vs. *IDP*	0.22
8	*IDP* vs. **UCB** (Engineering)	**0.00**

Note: Items a-d are a subset of Item 1 (US Universities). The undergraduate groups are each represented with a different style type to highlight the groups being compared: KAIST, **UCB**, CCA, *IDP*

Table 4.6 Learning Style Distribution of Undergraduate Population by Institution

	KAIST		UCB (Engr)		UCB (BA)		IDP		CCA	
Accommodating	50	12%	6	7%	4	11%	39	22%	5	17%
Assimilating	85	21%	21	23%	5	14%	27	15%	5	17%
Balanced	137	34%	24	26%	10	27%	81	45%	8	28%
Converging	115	28%	40	43%	17	46%	29	16%	10	34%
Diverging	19	5%	1	1%	1	3%	3	2%	1	3%
Grand Total	**406**	**100%**	**92**	**100%**	**98**	**100%**	**179**	**100%**	**29**	**100%**

Table 4.7 Learning Style Distribution by Ethnicity

	Ethnicity	p-value
1	Asian vs Non-Asian	0.36
2	White vs Non-White	0.21
3	Hispanic vs Non-Hispanic	0.28

People in the business field are expected to have an accommodating preference; our population shows nearly 50% convergers. Likewise, those in the arts field reported as having a diverging learning style preference. In our art student population (CCA), the diverging learning style is the least represented. We might expect the IDP students to match closely with the art field as well, but they are mostly comprised of people with balanced learning style. That this IDP population has a much lower representation of converging learners does imply that its students are at least different from engineering and business students. Regardless, these results reveal that our innovation-oriented population is quite different from the general population.

4.1.2.3 Comparison of Learning Styles by Ethnicity

Learning styles and ethnicities were also explored, but no statistical significance ($p<0.05$) was found for any of the populations in which ethnicity information (Table 4.7) was collected. This is an intriguing result, as there was significance when comparing the undergraduate population at a Korean university with the aggregate populations at U.S. universities. Perhaps this speaks to the culture that a person is raised in – the UCB student population is ethnically diverse but many are raised in American culture. These comparisons were chosen to evaluate whether a specific ethnic group had an influence when compared with collective population.

4.2 Industry

In this section, learning styles of industry professionals in the innovation-oriented population are examined. It is important to understand this group because these are design thinkers in the corporate world, actively creating products used in industry. Does this group match the profile of the general populace or do they look like a designer population might? How they leverage diversity in their teams will be reflected in the quality of their products.

4.2.1 Survey Population and Methods

Data were collected from a mix of 2,070 professionals primarily in the business field. These participants come from companies ranging from a large international consultancy (primarily Australians) to a financial services provider (U.S.-based, but with multinational participants) to a large pharmaceutical company (U.S.-based, with U.S. and European participants). Table 4.8 presents a summary of major groups represented in the industry population.

Table 4.8 Industry Population[5]

	Total
International Consulting Firm (ICF)	745
Executive Program	229
Product Management Program	786
Various Technology Companies	310
	2070

[5] Section 4.2 covers all the industry data as described in Chapter 3.

4.2.2 Results

4.2.2.1 Comparison of Learning Styles by Gender

Table 4.9 displays the distribution of learning styles by gender in industry. Table 4.10 presents the p-values calculated from Pearson's Chi-Squared test for categorical data. Results show that there is a statistically significant difference ($p \leq 0.05$) in learning styles between males and females for the overall industry population as well as for two of the specific groups: a large international consultancy and the Product Management Program participants.

Table 4.9 Distribution of Learning Styles in the Entire Industry Population

	Entire Industry Population			
	Female		Male	
Accommodating	76	13%	109	7%
Assimilating	126	21%	431	29%
Balanced	170	28%	339	25%
Converging	214	35%	554	38%
Diverging	22	4%	29	2%
Grand Total	**608**		**1462**	

Table 4.10 Statistical Significance of Gender Differences in Each Industry Population

	p-value
Entire population	**0.00**
Large International Consultancy Firm	**0.01**
Executive Education Program	0.11
Product Management Program	**0.00**

Table 4.11 Product Managers by Undergraduate Disciplines

	Product Managers					
	Female		Male		Total	
Accounting	4%	3	2%	4	2%	7
Applied & Fine Arts	1%	1	1%	3	1%	4
Business	20%	16	15%	31	16%	47
Computer Science	16%	13	17%	35	17%	48
Engineering	26%	21	36%	75	33%	96
Science/Math	20%	16	13%	28	15%	44
Social Science	13%	10	15%	32	15%	42
Grand Total		80		208		288

Table 4.12 ICF Learning Styles by Gender

	International Consulting Firm					
	Female		Male		Total	
Accommodating	32	17%	52	9%	84	11%
Assimilating	29	16%	126	22%	155	21%
Balanced	50	28%	132	24%	182	17%
Converging	68	37%	236	42%	304	41%
Diverging	5	3%	15	3%	20	3%
Grand Total	184		561		745	

Table 4.13 Learning Style Means and Standard Deviations by Gender

		AC	AE	CE	RO
Male	Mean	36.1	31.8	25.5	26.6
	Standard Deviation	6.51	6.89	6.73	7.34
Female	Mean	33.4	33.5	26.8	26.3
	Standard Deviation	7.13	5.66	7.81	7.77

Some insight might be gained by looking at the educational background of the working professionals. Unfortunately, this information was not captured for the entire industry pool, but the undergraduate majors are presented in Table 4.11 for the Product Managers. It can be seen that engineers make up only about one-third of the population and the rest of the group is equally divided between the remaining majors. In the student analysis above, statistical significance was found in gender analysis only for the less technical groups. This aligns with the results with Product Managers, who are majority non-engineers and also show that gender does matter in learning styles.

The large, international consultancy firm (henceforth referred to as ICF) is comprised of 184 females and 561 males. Table 4.12 shows the learning styles distribution of the population. However, even more interesting are the actual learning style profiles (Figure 4.1), which highlight a slight gender difference in how the ICF group perceives information, with females showing greater preference for concrete thinking while males hover higher in the abstract region.

The numerical scores of the four dimensions (AC, AE, CE, RO) were additionally analyzed for significance, beginning with a Kolmogorov-Smirnov test on each dimension to confirm normal distribution across the entire population (Figure 4.2). The mean scores and standard deviation are presented in Table 4.13. A Hotelling's multi-variate T-test analysis was then run for each dimension, by gender (e.g., AC female, AC male, AE female, AE male, etc) with the following results: $T^2 = 2.4934$ and $p = 0.04$. These findings further support that there is a significant difference between men and women in their learning style scores.

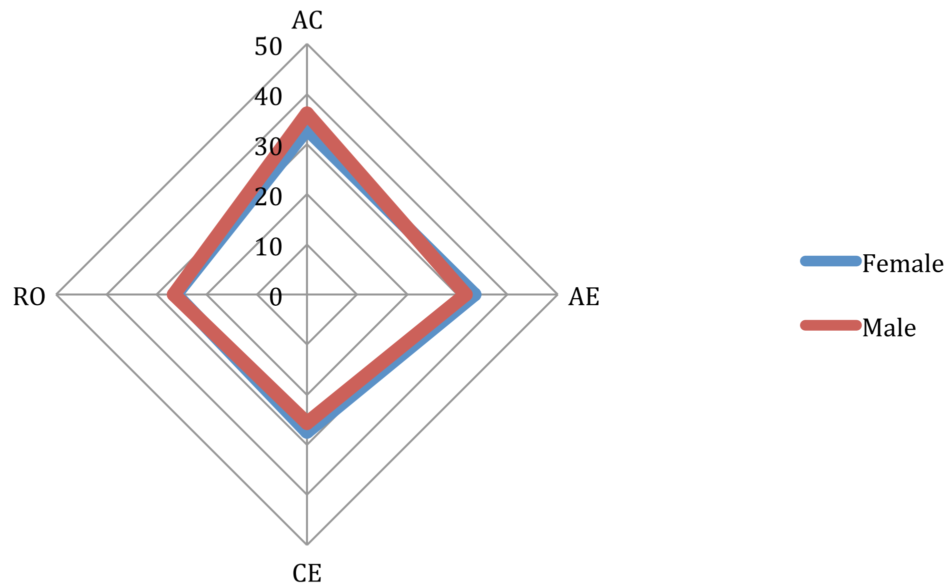

Figure 4.1 ICF Learning Style Profile by Gender

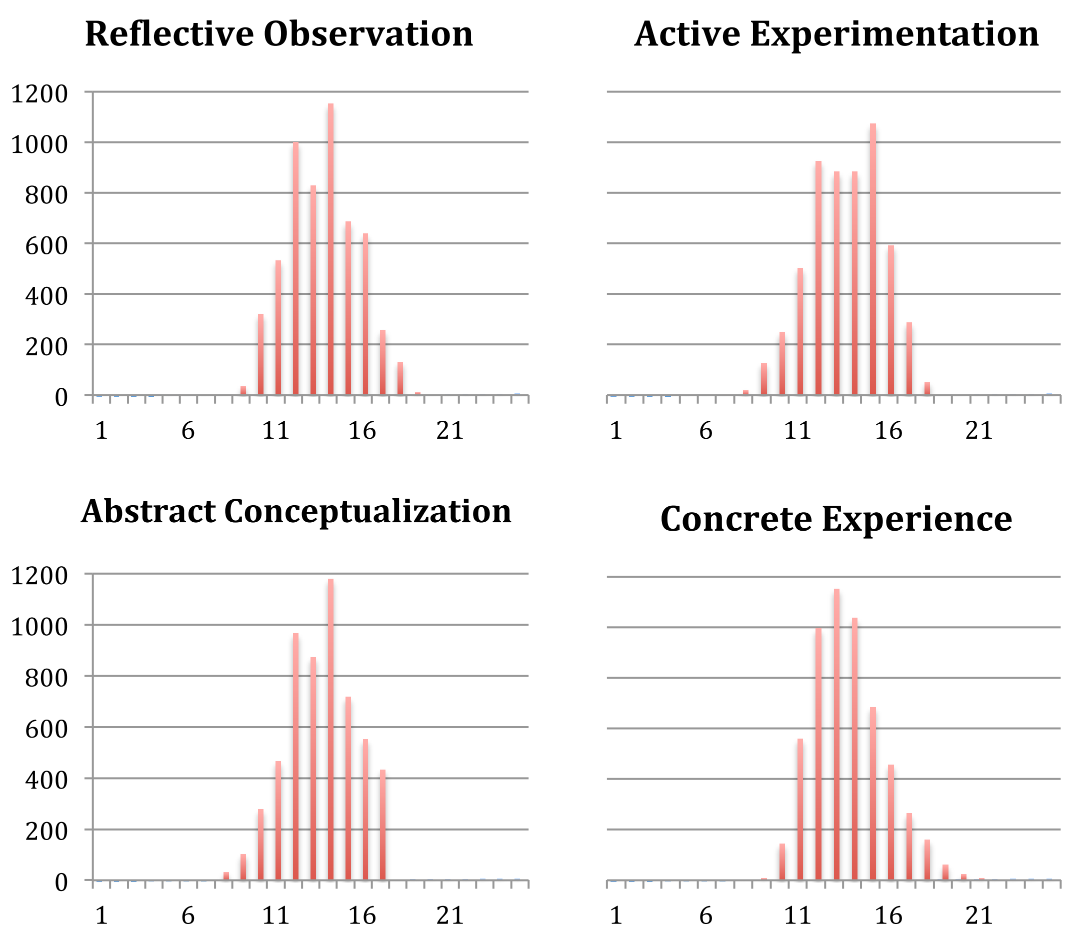

Figure 4.2 Kolmogorov-Smirnov Normal Distribution Plots (# people vs score)

It is seen with both students and professionals that gender affects learning styles. This is thus an important factor to consider when forming design teams, as it may influence how an individual contributes in the design process. For instance, women (as accommodators) might perform best in the solutions phase of the project, so it is prudent to emphasize their role in that phase. Ultimately, this understanding can help everybody optimize the design process.

4.2.2.2 Learning Style by Job Level

In this section, I investigate the learning styles by job levels, for executives versus individual contributors. Executives are those who manage others and have decision-making authority; this group is made up of CEOs, Vice Presidents, Directors, and other equivalent roles. Individual contributors are non-management members with day-to-day responsibilities; this group is made up of engineers, analysts, and other equivalent roles. A T-test analysis gives p-value of 0.87, revealing that job level does not affect the four dimensional scores.

This result is not exactly congruent to what might be expected given the different tasks and responsibilities of the two roles. For instance, executives might be more tasked with decision-making in tenuous situations (accommodating) or may need to build and maintain solid partnerships and communication (diverging), whereas individual contributors must have strong problem-solving skills (convergent). However, in this population, the makeup is very similar with converging learners dominating and a paucity of diverging learners.

Figure 4.3 displays learning style distribution of contributors and executives for (1) the ICF group, (2) employees in other companies, and (3) graduate students (e.g., their professional role prior to enrolling in graduate school). Figure 4.4 maps the overall profile of executives and of contributors in ICF and Figure 4.5 displays the same for other working professionals and for graduate students. All three groups have nearly identical profiles, as expected with no statistical significantly different results.

4.2.2.3 Learning Style by Department

The ICF is made up of eight departments that each provides a different type of service to the customer. For each of these eight groups, the learning style breakdown is presented in Figure 4.6; the results are striking. Despite each department having a different goal and service, the profiles are mostly the same. This could imply that regardless of the end product, the ICF team as a company follows the same process to its goals.

There is one exception: Group E, which presents a rarely seen breakdown of Divergers being more highly represented than Convergers, and Balanced learners dominating. In fact, this group is internal facing and must support the needs of every group across the entire firm. This aligns with the diverging learning style and the accompanying ability to identify with different viewpoints. So although this group does not match the profile of the rest of the company, it is made up of members with the best learning style preferences for fulfilling their responsibilities. Figure 4.7 presents the learning style profile of the entire industry population compared to the ICF group.

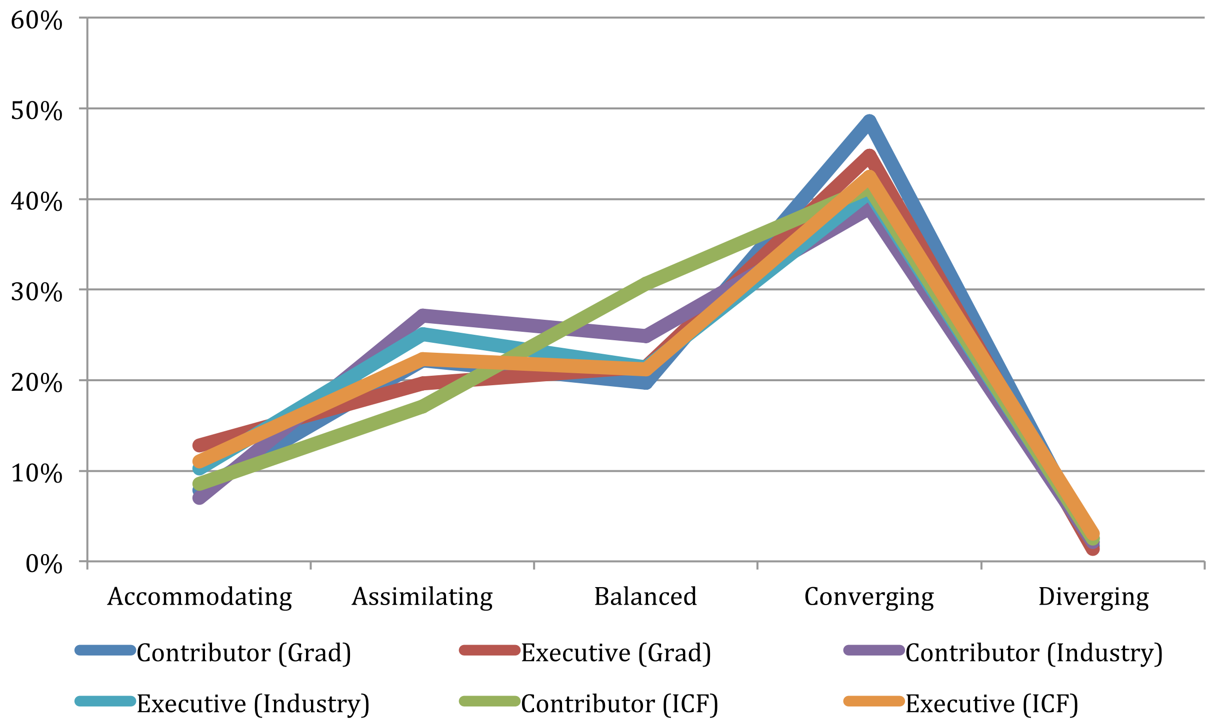

Figure 4.3 Learning Styles by Contributor versus Executives

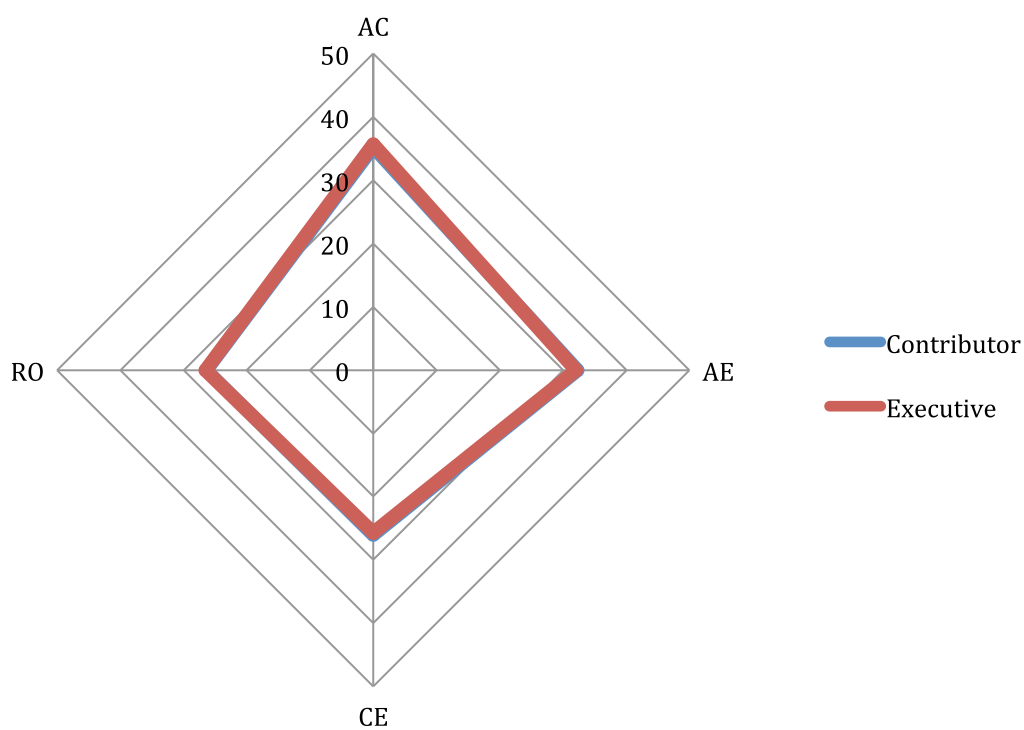

Figure 4.4 ICF Learning Style Profile by Job Level

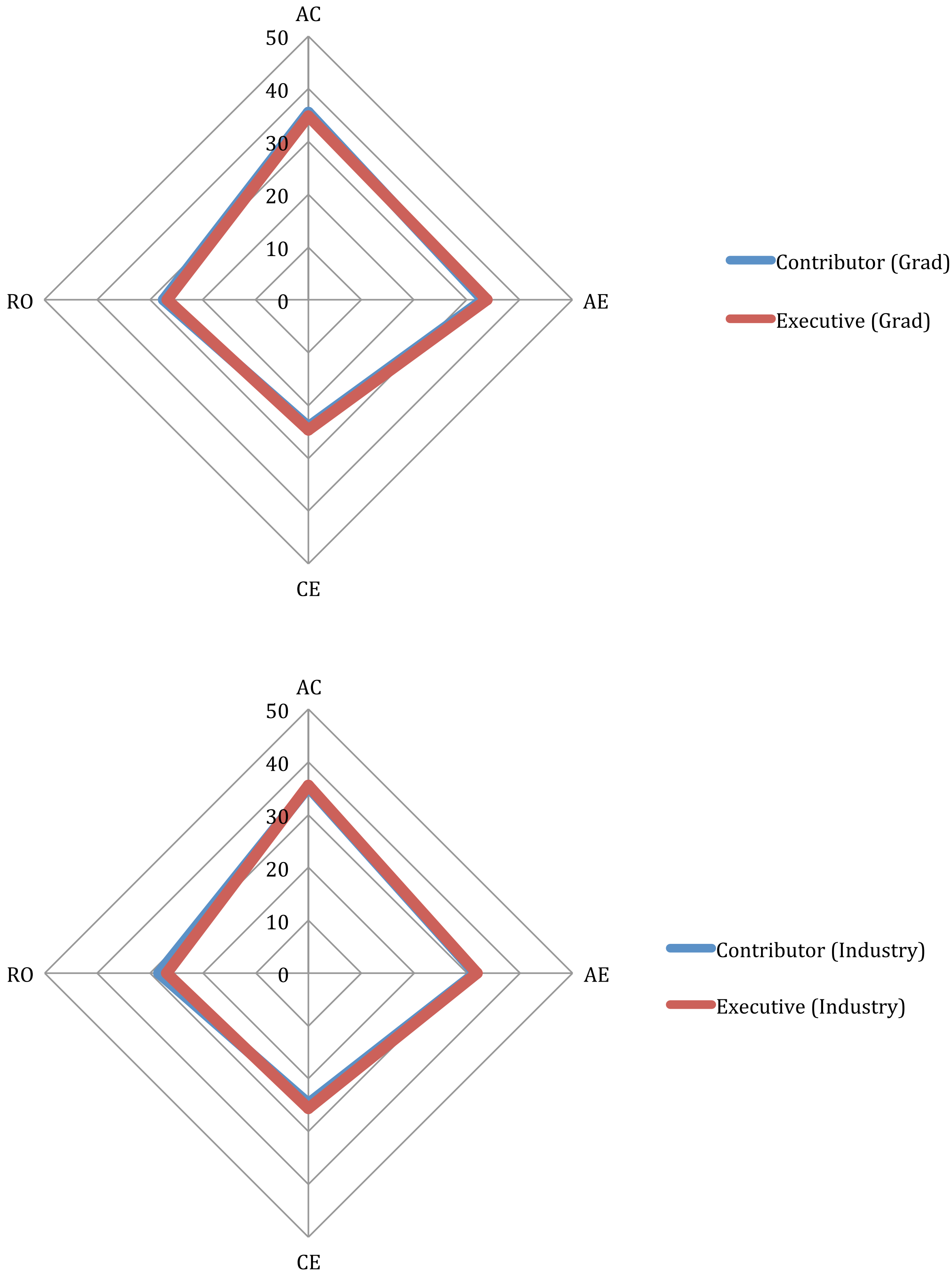

Figure 4.5 Learning Style Profile by Job Level, Graduates and Industry Professionals

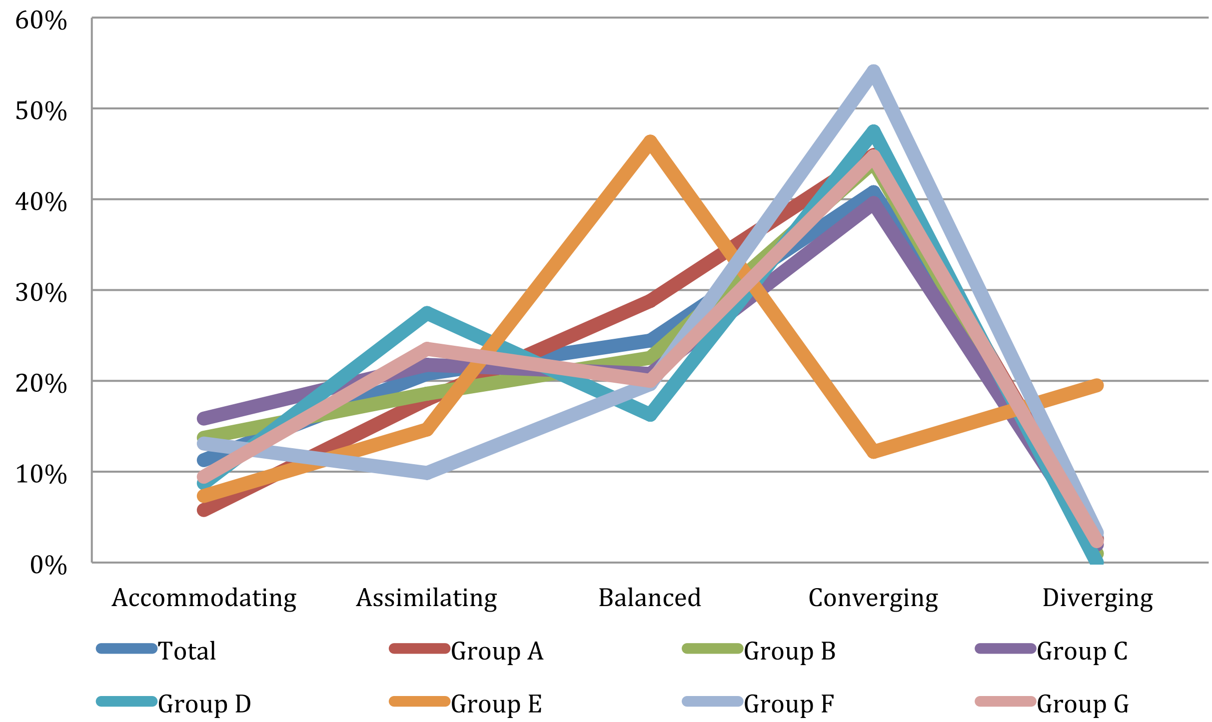

Figure 4.6 ICF Learning Style Profile by Department

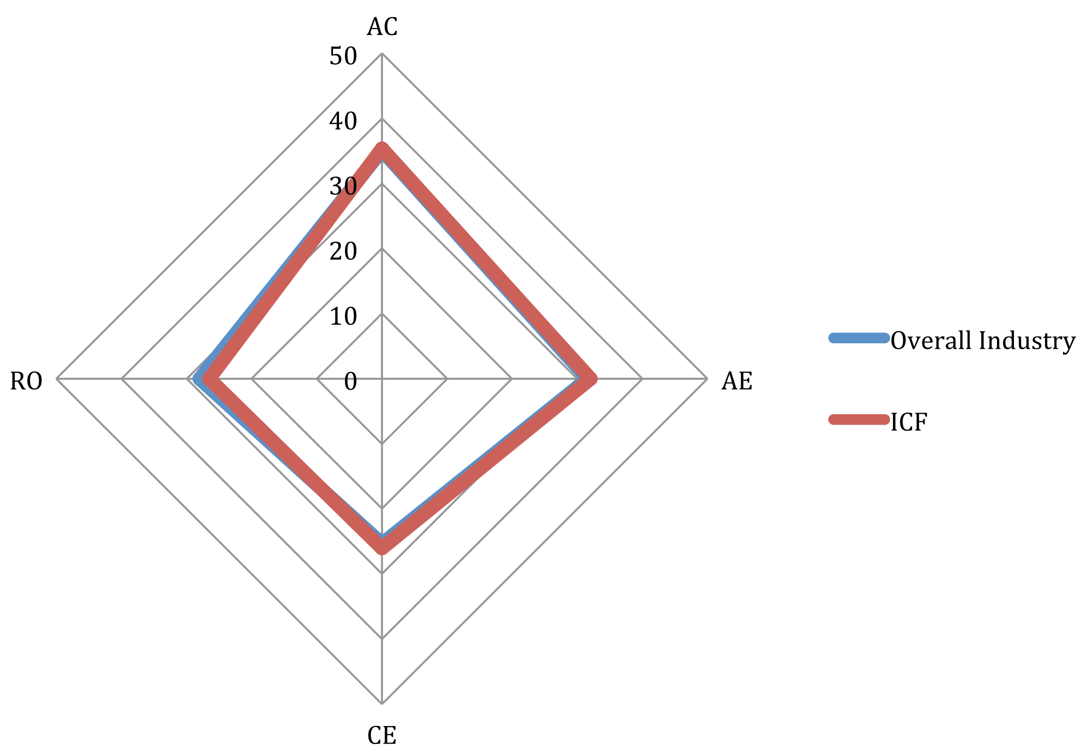

Figure 4.7 Learning Style Profile of ICF versus Overall Industry

4.3 Combined Students and Industry

In this section, student and professional groups are combined and the entire population described in Chapter 3 is evaluated. This characterization is what will give the broadest view of this innovation-oriented population, and set up the research basis for understanding how learning style diversity affects design outcomes.

4.3.1 Survey Population and Methodology

In this section, the entire research population is evaluated. The breakdown is in Table 4.14.

Table 4.14 Overall Survey Population[6]

	Total
Undergraduate	1623
Industry	2070
Graduate	2993
Grand Total	**6686**

4.3.2 Results

4.3.2.1 Perception and Processing Continuums

Previous research has shown that males are more abstract than females and that there are no significant gender differences in action over reflection (Kolb, 2005). To measure this in the population, the scores are examined along each axis: Perception Continuum, AC-CE and the Processing Continuum, AE-RO. The tendency for abstract thinking is quantified by subtracting the CE (concrete) score from the AC (abstract) score, with a higher result representing greater preference for abstract over concrete thinking. Active processing is evaluated by subtracting the RO (reflective) score from the AE (active) score, with a higher result showing greater preference for action over reflection. Results for the entire female and male populations are displayed in Figure 4.8.

There is a visible difference in the AC-CE (abstract) scores, with men showing a higher AC-CE value than women. However, the AE-RO (active) scores are nearly equal; men and women have equal preferences for action and reflection. In Figure 4.9, we observe higher AC-CE scores in graduates, but lower AC-CE scores in working professionals. What is fascinating is the implication that abstract people might be more attracted to academics, while less abstract thinkers tend more towards industry. Indeed, people who actively design new products in

[6] This section presents an analysis of the entire research test bed described in Chapter 3 to provide insights of the collective design population.

industry probably enjoy being involved in new experiences (CE), while researchers excel at creating and refining theories to explain observations (AC). Once understood, it is possible to leverage these preferences in any design that is created.

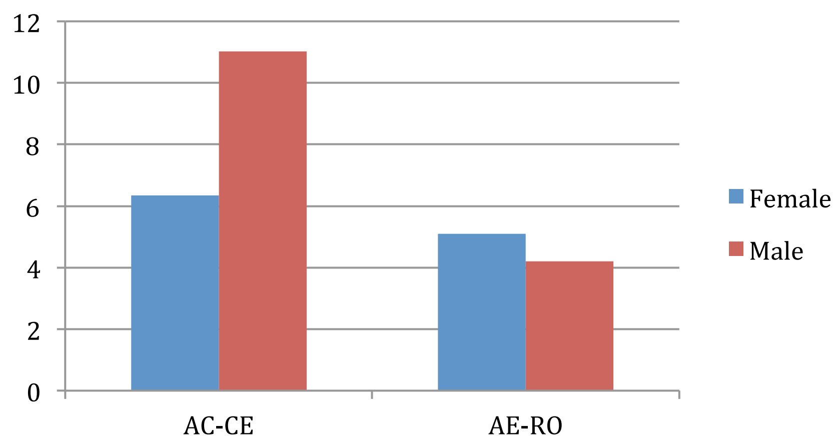

Figure 4.8 AC-CE and AE-RO Scores, by Gender

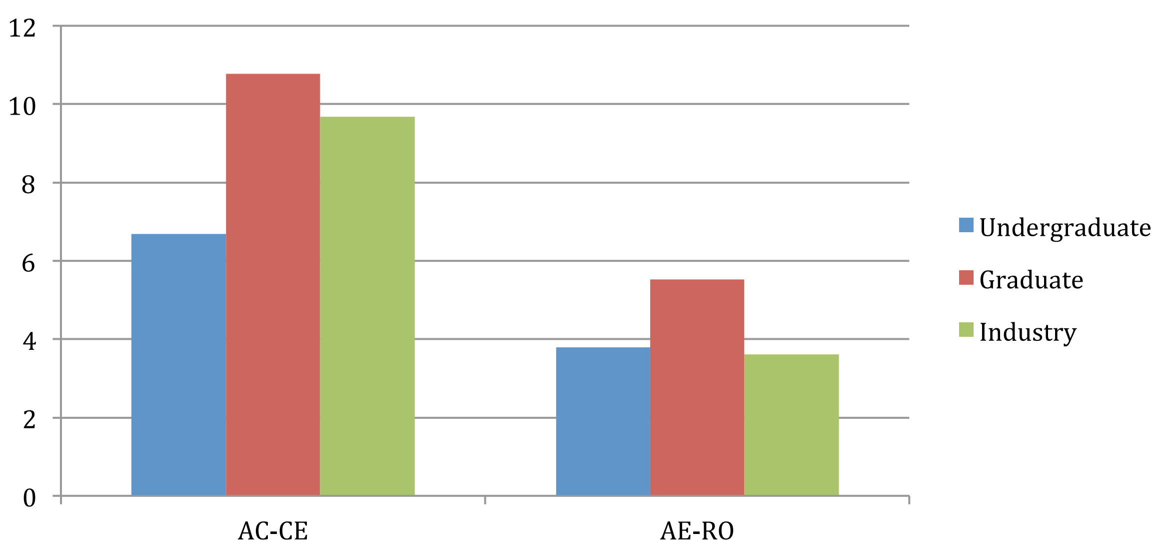

Figure 4.9 AC-CE and AE-RO Scores, by Status

4.3.2.2 Learning Styles of Consecutive Populations

In this section, the makeup of a specific program or course over consecutive years is examined to explore whether each new group maintains the same profile in the specific program, regardless of time. Figures 4.10-4.18 map the learning style profiles of each group in this scenario. Note that these are not longitudinal studies of one population over time, but rather a comparison of new student and professional groups participating in a specific program or course over consecutive years.

Table 4.15 Learning Style scores of MBA students

	AC	AE	CE	RO
FTMBA (2012-2016)	35.5	33.7	24.0	26.9
EWMBA (2011-2015)	34.9	32.6	24.1	28.4
MBA program in Europe (2012-2013)	34.0	32.3	26.4	27.3

What is fascinating to note is that each group mostly maintains a consistent learning style profile over a number of years, despite each year consisting of entirely different people. For instance, the Full-Time MBA students have a nearly identical learning style profile between 2012 and 2016 (Figure 4.11). The same can be said for the learning style profile of IDP students over three years (Figure 4.17). Yet, profiles do vary when comparing between different groups, such as with the Full-Time MBA and IDP students.

Figure 4.10 maps the learning style profile of every group on one grid. While the collective profiles lean into the Converging quadrant – which is not altogether surprising given the above observations of the population – nuances can be seen between the groups.

The Full-Time MBA student profiles are nearly identical to that of the Evening-Weekend MBA students (Figure 4.12). This is perhaps expected, given that both groups are pursuing MBAs and may thus have similar inclinations. Students in a business school in Europe (Table 4.15) have a similar profile, but are the most dissimilar of the three different MBA groups. Perhaps this is due to a cultural difference.

The ME110 and NPD populations also share very similar profiles. This could be due to the curriculum being similar (but at undergraduate and graduate levels) between the two classes, therefore attracting like-minded learners. That a portion of the NPD class is made up of MBA students could also explain why the NPD profile matches so well to FTMBA students. Comparing between all populations (Table 4.16), the three most different profiles are those of the IDP students, an Executive Program in Asia, and a business school in Europe. In fact, of all the populations, they also have the most different backgrounds – (1) students primarily engaged in an integrated design program in a liberal arts university, (2) executives from Asia, (3) MBA students in Europe.

This analysis is perhaps most telling of the targeted populations within each group. The population shows majority convergers, and looking over time, the profiles of the groups are all identical. In order to add diversity into the population, perhaps the path to go is to transform the admission process or the interview process or overall guidelines, to expand into finding people that are different from the typical profile. This will benefit all design-oriented populations. It is clear that all of these programs want a certain fit of person, which may not be the correct one for all of design. This may also force people to conform to certain profiles to be accepted, rather than be different and awarded for it.

Table 4.16 Learning Style Scores of All Populations

	AC	AE	CE	RO
FTMBA (2012-2016)	35.5	33.7	24.0	26.9
NPD (2010-2013)	34.2	34.3	23.8	27.5
Executive Program in Asia (2012-2015)	36.2	29.6	24.7	29.5
ME110 (2013-2015)	33.2	34.3	23.2	29.2
IDP (2011, 2014, 2015)	28.9	34.0	26.2	31.0
EWMBA (2011-2015)	34.9	32.6	24.1	28.4
MBA program in Europe (2012-2013)	34.0	32.3	26.4	27.3

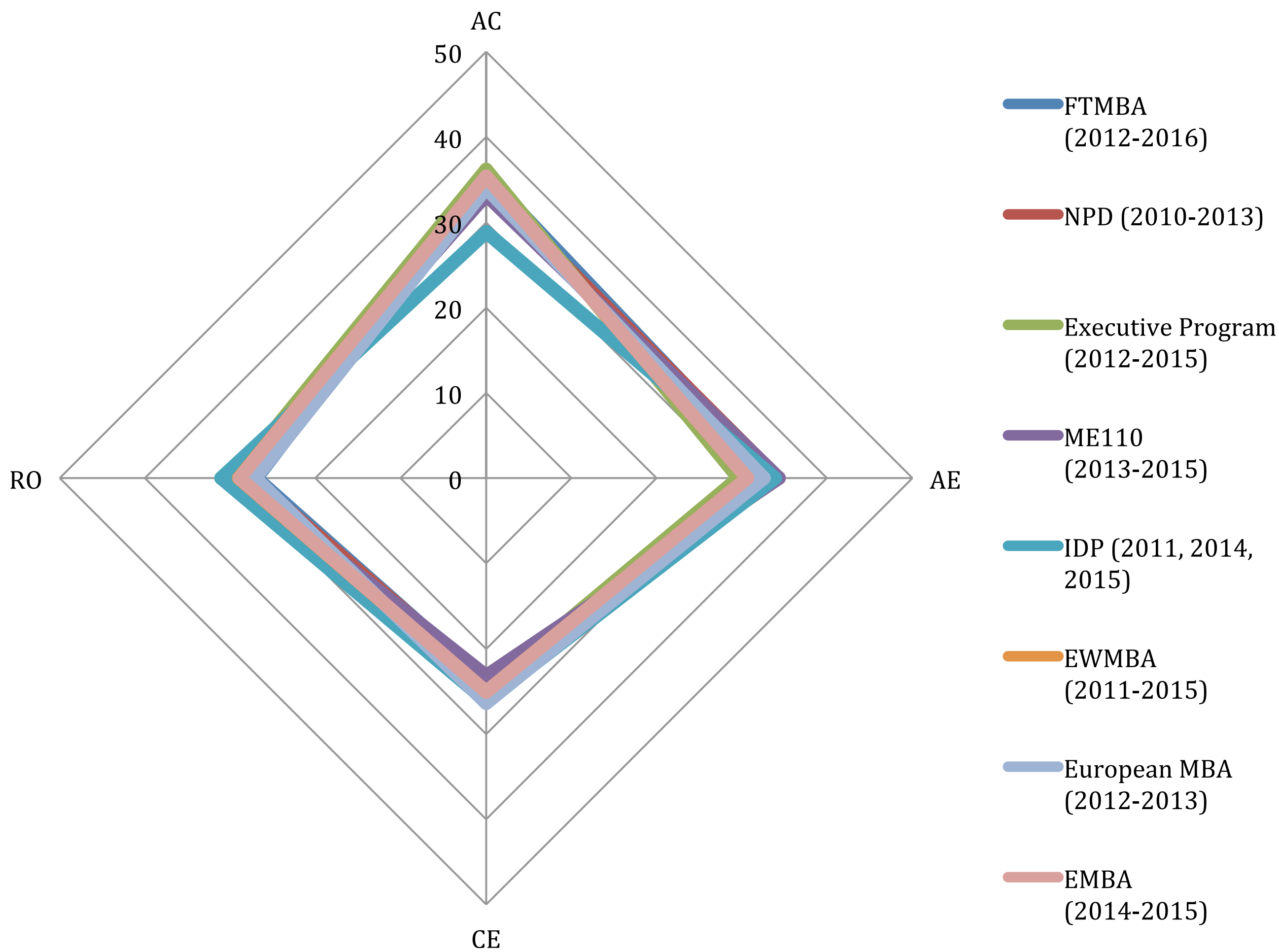

Figure 4.10 Overall Learning Style Profile for Each Group

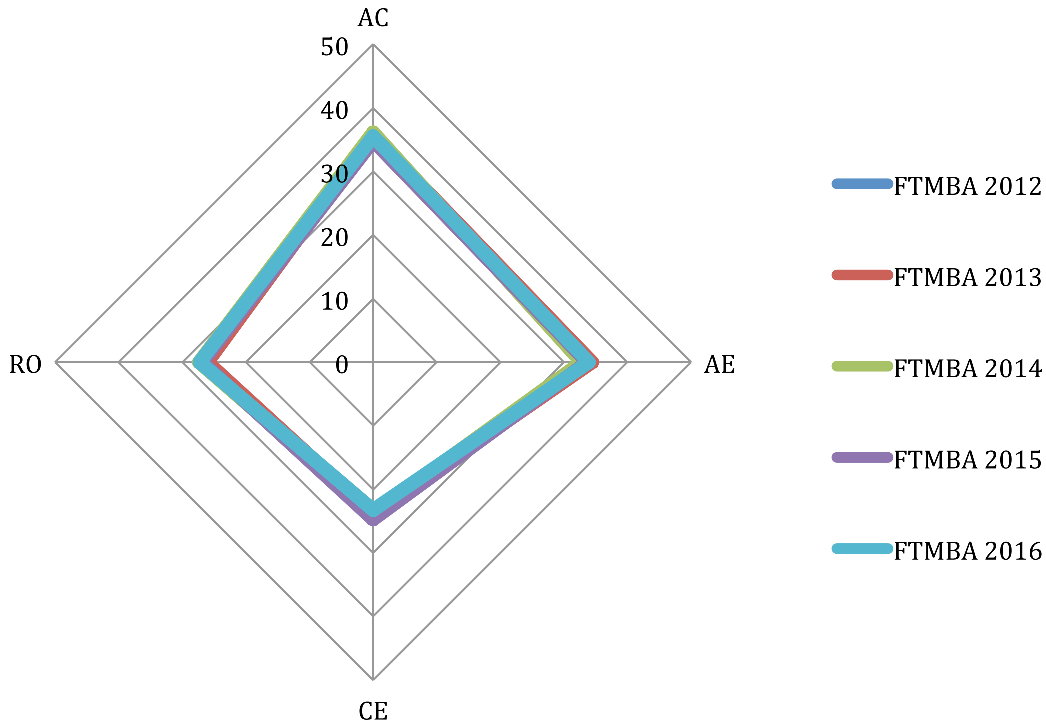

Figure 4.11 Learning Style Profiles of FTMBA 2012-2016

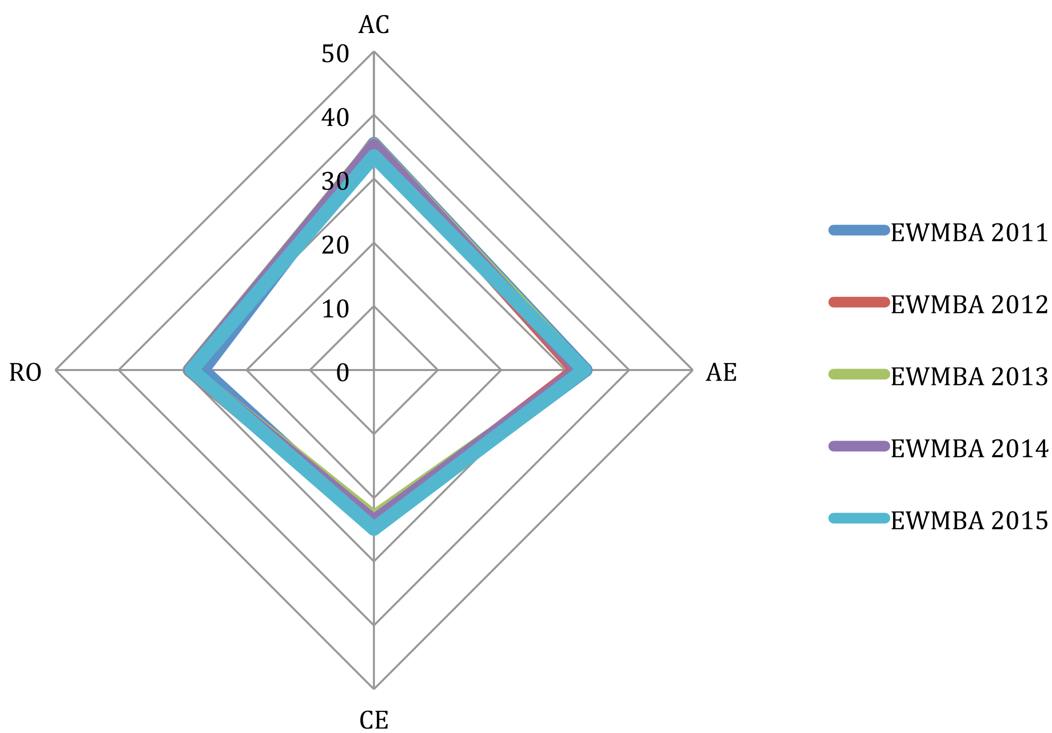

Figure 4.12 Learning Style Profiles of EWMBA 2011-2015

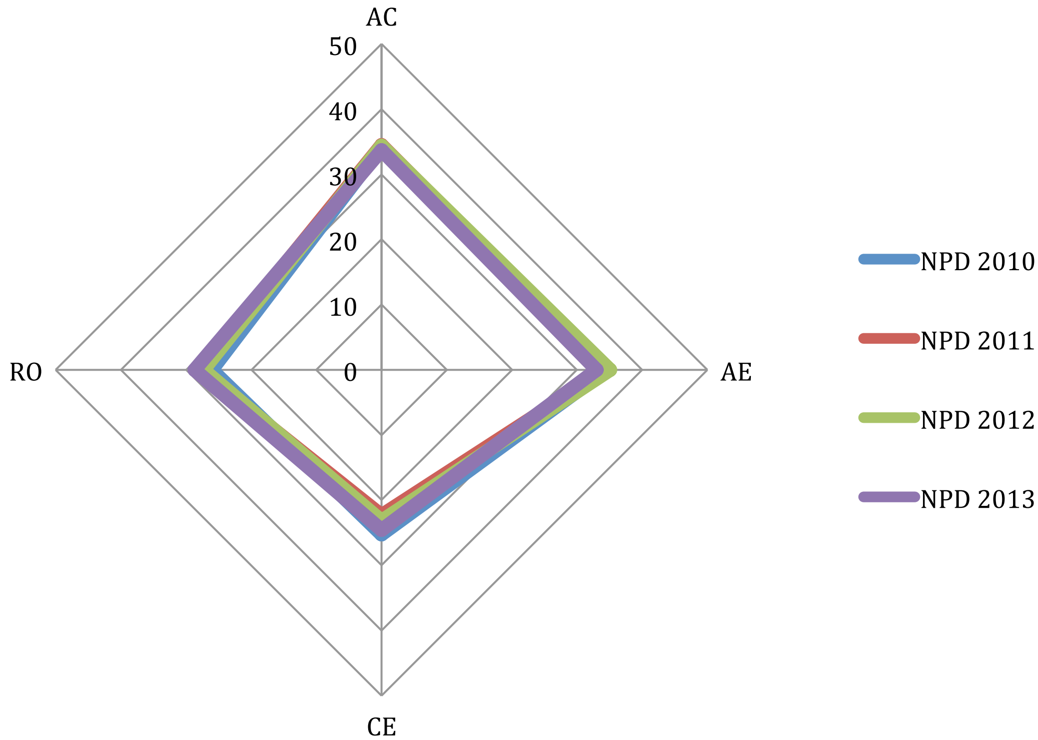

Figure 4.13 Learning Style Profiles of NPD class 2010-2013

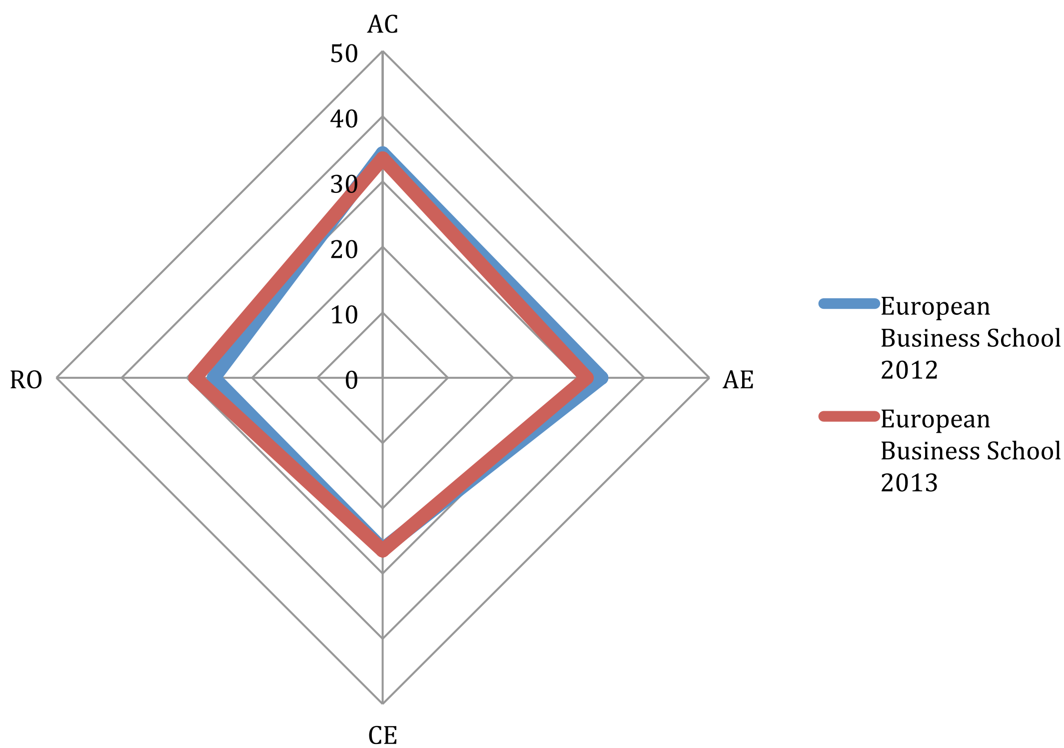

Figure 4.14 Learning Style Profiles of European Business School 2012-2013

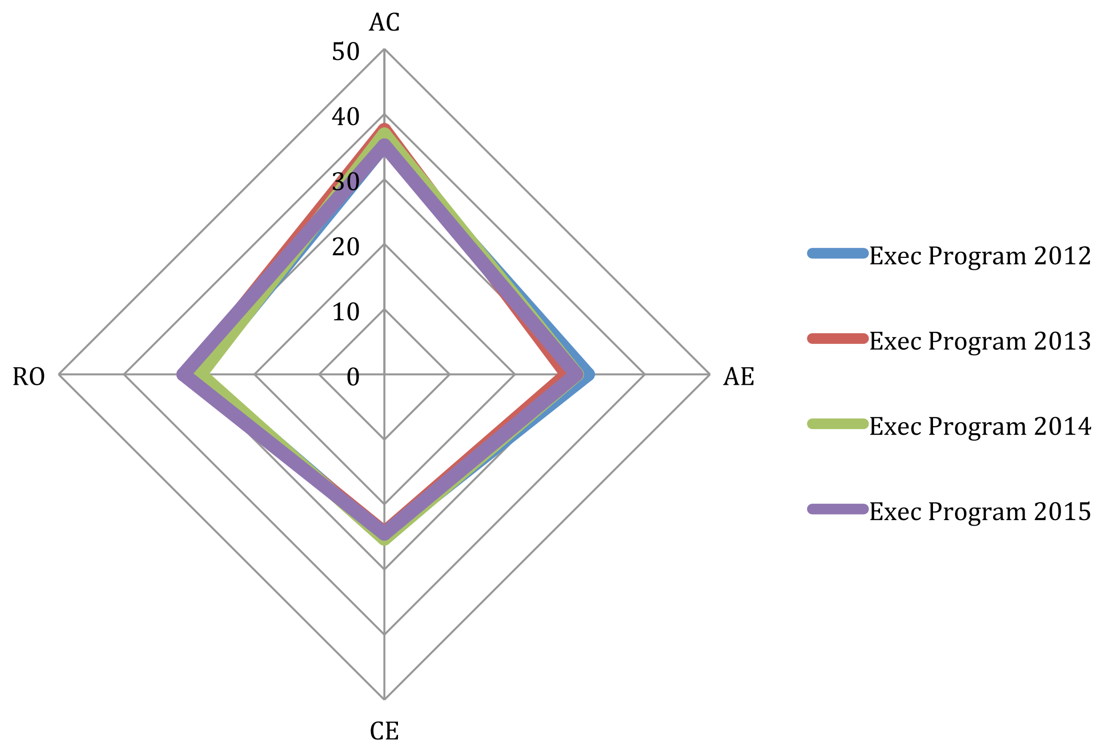

Figure 4.15 Learning Style Profiles of Executive Program in Asia 2012-2015

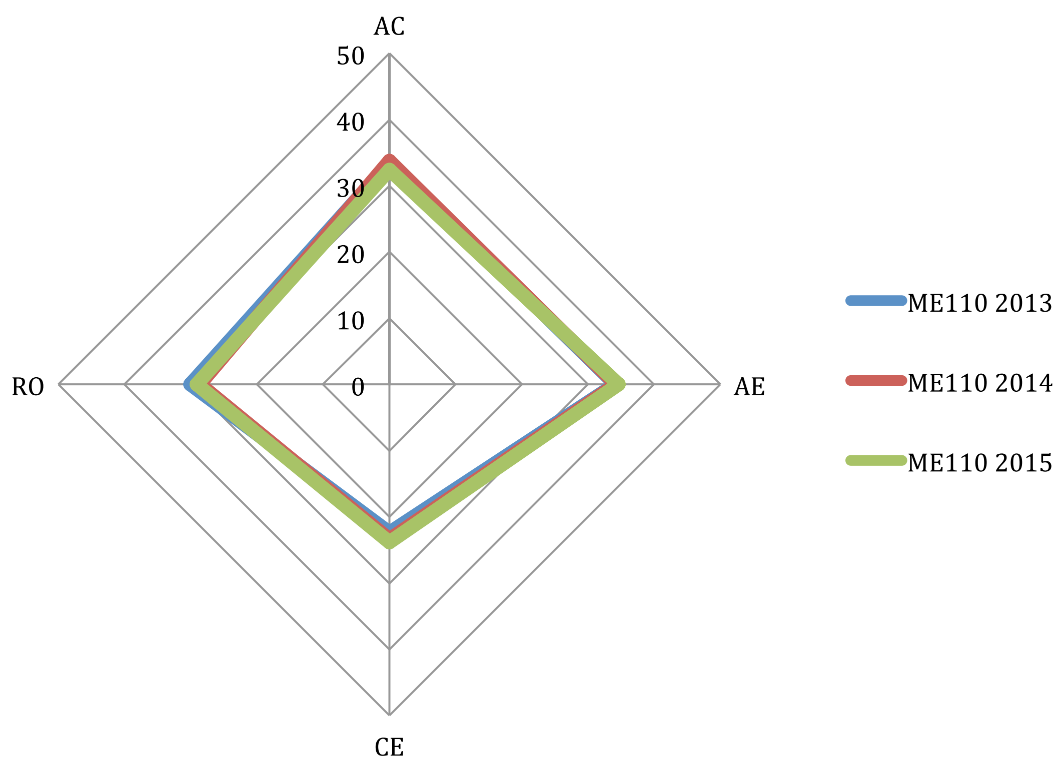

Figure 4.16 Learning Style Profiles of ME110 2013-2015

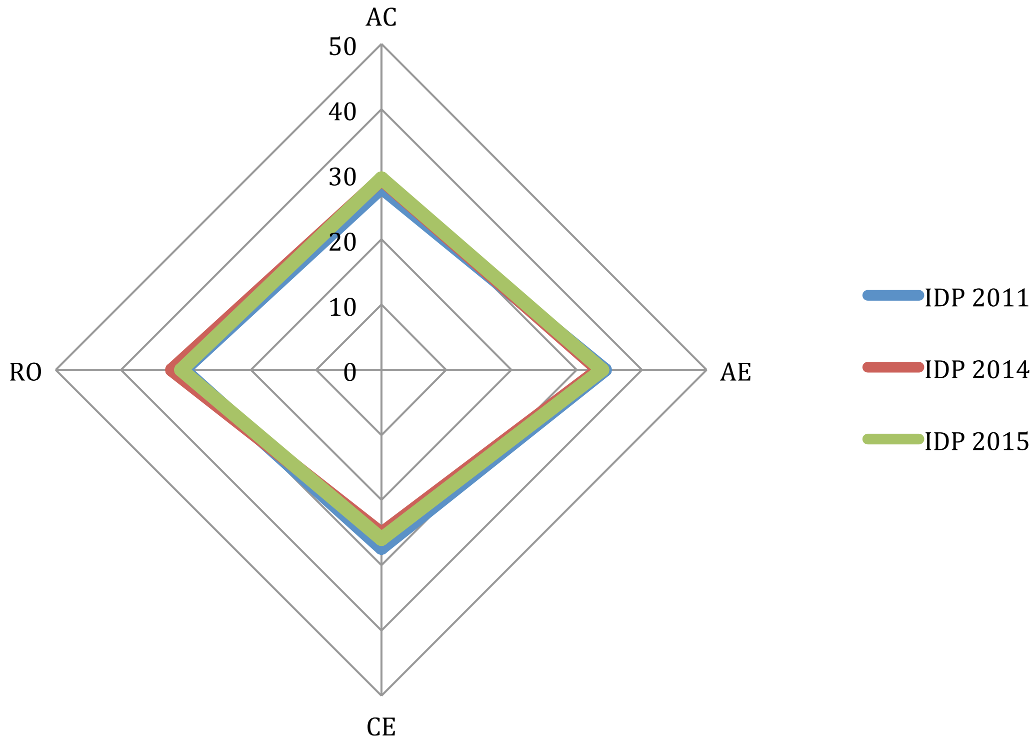

Figure 4.17 Learning Style Profiles of IDP 2011,2014,2015

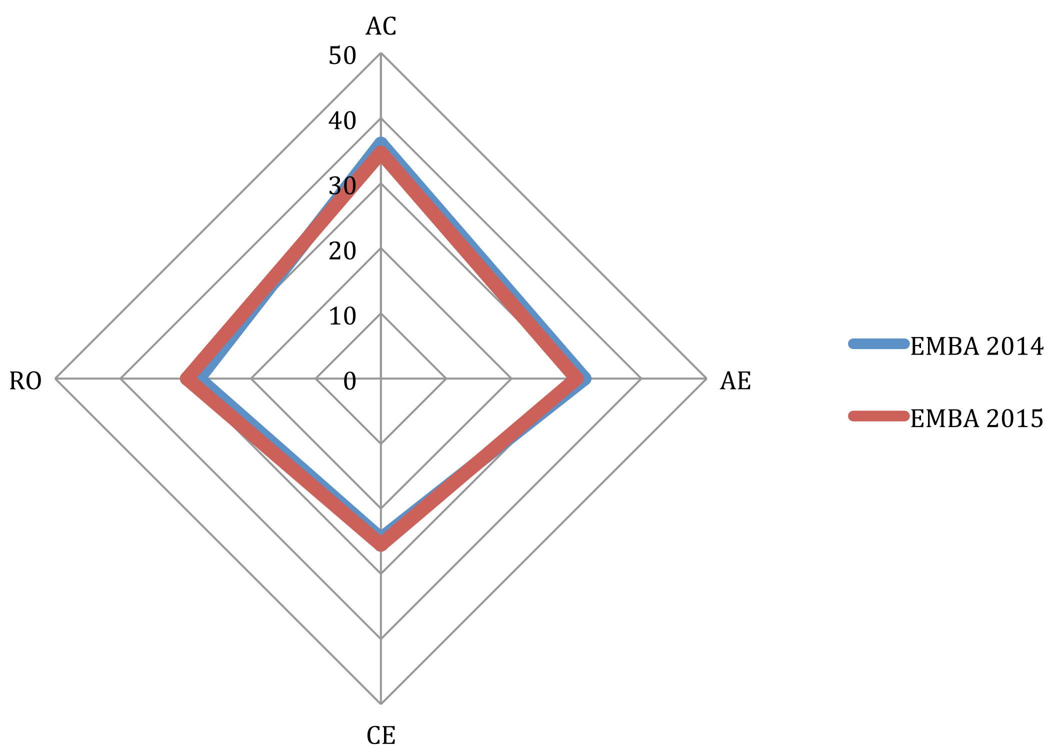

Figure 4.18 Learning Style Profiles of EMBA 2014-2015

4.4 Conclusions and Recommendations

Previous research has shown that women and men have different learning styles, with females more strongly represented in the divergent and accommodating styles than males. This study provides more nuanced insight into this general research. Although it was found that men and women in business school have statistically significant different styles, with more women who are accommodating and diverging learners, in the engineering student population these differences did not show up. This raises the interesting question of whether or not engineering education as presently configured either minimizes the importance of these learning styles, or teaches approaches that primarily leverage the assimilating and converging learning styles instead, thus potentially attracting more males than females to the profession particularly at the graduate level. This is a topic that deserves more research.

Perhaps more concerning is the lack of representation in this dataset of people with diverging learning styles. Those with a diverging learning style are good at seeing situations from multiple different perspectives. They are characterized as imaginative, able to take many perspectives, having broad cultural interests, information seeking and good at understanding people and recognizing problems. Increasing interest in "customer-focused design" suggests that design teams will need the abilities to be more sensitive to others, listen with an open mind, and imagine the implications of ambiguous situations that divergers have. This will have to come either from admitting more students with diverging learning styles, training them in diverging skills, or putting them on teams with divergers from other disciplines on the campus. More research is needed to understand the broader implications of the lack of divergers in the student population on curriculum design.

Convergers are the dominant population in our study, across all sectors. Convergers are generally strongest at problem-solving and decision-making, and excel at taking standardized tests. They are good at finding practical applications for ideas and theories and at hypothetical-deductive reasoning. In contrast with their fellow abstract thinkers, e.g., those with the assimilating learning style, they are action oriented and focus on problem solving rather than problem framing.

This dominance of convergers raises yet another set of questions about how and what is taught in the engineering and business disciplines. In the increasingly complex world graduates will face, it is possible that they will need to be able to both frame and solve problems. This suggests in turn that there be more focus in school on having students take on the framing of complex problems before they are asked to solve them. Again, this requires additional research to understand the extent to which students are asked to do problem framing today, and how well they are equipped to do so, and into where their converging learning styles are first developed.

This dataset also raises questions of pedagogy. Schaller et al. (2007) found that different Kolb learners have statistically different preferences in learning activities. Assimilators prefer self-directed learning with "multimedia content in a topical or thematic structure". Convergers prefer activities that "involve analysis and deductive reasoning to reach a logical conclusion". Accommodators prefer "role-playing activities that allowed users to adopt a persona and interact with characters" as well as "open-ended inquiry and experimentation, with a personal creation as the product of the experience”. Divergers, however, preferred discussion activities that allowed communication among users and subject experts. These empathic skills found in both divergers and accommodators are considered critical in human-centered design and user research. The presence of different learning styles, particularly across genders, suggests that pedagogy accommodate different approaches, both as directed at individuals and at teams. Once again, this suggests the need for additional research. Are the pedagogical approaches used in the institutions in this study drawing different learning styles? Or are they changing students in the program to adopt different learning styles than the ones with which they entered? The striking difference between the KAIST student population and the others most starkly raises these questions.

This research suggests that education may need to consider the different learning styles of student populations, particularly gender differences. Differences by ethnicity in the populations studied were not significant. In future research, it would be interesting to examine the industry population by the disciplines from which the participants came (e.g. Business, Engineering) to compare with the student population and observe any changes between academia and practice. Where changes occur, it would be worthwhile to study whether they are happening as a result of selection bias, or by training within the companies themselves.

Chapter 5

Learning Styles and ABET Assessment

In Chapter 4, I evaluated the population as a whole and provided insights into the nuances of designers with respect to different diversity factors. In this chapter, I will examine how learning styles affect how students self-rate their design and engineering skills, skills which are valuable to their performance in the design process. More specifically, I explore the confidence levels in ABET skills among lower division students in project-based design courses offered at the University of California at Berkeley and the Korea Advanced Institute of Science and Technology. I draw comparisons of confidence in these engineering and design skills by country and gender, as well as learning styles.

5.1 Survey Populations and Methods

Most of the data were gathered from design courses at research universities in Korea and the United States. The Korean data are from "ED100: Introduction to Design and Communication," a freshman-level course offered at the Korea Advanced Institute of Science and Technology (KAIST). ED100 is a required course for all freshmen at KAIST, regardless of major, and focuses on the fundamentals of conceptual design and critical thinking. Although students do not declare majors in their freshman year, over 50% of the students at KAIST eventually graduate with a B.S. degree in computer science or engineering. In contrast, only 24% of B.S. degrees granted in Korea are related to engineering.

Table 5.1: Breakdown of Course Participants

	E10			**ED100**	
	Spring 2008	Spring 2009	% by Gender	Fall 2010	% by Gender
Women	45	34	25%	133	33%
Men	129	108	75%	274	67%
Total	174	142	100%	407	100%

The data from the United States are from lower division students in "E10: Introduction to Engineering Design and Analysis", a course offered at the University of California at Berkeley that teaches freshmen about engineering design, analysis, and practice. E10 is split into three parts over the semester. The data are collected from students participating in the six-week module entitled "Sustainable Human-Centered Design". Both ED100 and E10 are project-based courses, with teams of four to six members each. The projects are open-ended, real-world design challenges that allow students to explore a wide range of ideas in their design solutions. Although both courses are compulsory, ED100 is required for all freshmen while E10 is open to the campus but only required for engineering students. As a result, the ED100 students are expected to have a wider range of disciplinary interests. Table 5.1 shows the number of students from each class that participated in the study. Note that the percentage of female students in ED100 is somewhat higher than that of E10 (33% versus 25%).

The data were gathered from surveys that were administered at the beginning of the semester to the E10 students in Spring 2008 and Spring 2009 and to the ED100 students in Fall 2010. We included additional data related to Kolb learning styles collected over a range of ages from UC Berkeley in Fall 2010 and Spring 2011. Survey question topics cover standard demographics (gender, ethnicity, and discipline), Kolb learning styles, and past experiences with engineering or design (such as shop classes, CAD, sewing, design competitions, and engineering-related programs). Students were also asked to assess their strengths in design and engineering skills. The exact wording of the question was: “Based on your experiences and education thus far, please perform a self-assessment of how much you possess these traits”. The list of skills that followed is based on the learning outcomes as defined by ABET, which sets accreditation standards for American programs, and ABEEK, the Accreditation Board for Engineering Education in Korea (Chang, 2004):

- Analytical skills
- Creativity and practical ingenuity
- Ability to develop designs that meet needs, constraints, and objectives
- Ability to identify, formulate, and solve technical problems
- Communication skills
- Team skills
- Leadership and management skills
- Ethics and professionalism
- Recognizes need for an ability to engage in life-long learning
- Ability to design and conduct experiments, analyze, and interpret data
- Ability to learn and use the techniques and tools used in engineering practice
- Ability to recognize the global, economic, environmental, and societal impact of engineering design and analysis
- Ability to understand other cultures and engage in international collaboration.

This list builds on the learning outcomes that overlap in ABET and ABEEK criteria. In performing the cross-national analyses, we drew comparisons only for those skills on which both student groups self-rated. In the remainder of the paper, we will present the results of the survey and discuss possible implications.

5.2 Results and Discussion

5.2.1 Cross-National Comparison of Confidence in ABET-Related Skills

Table 5.2 presents the average self-confidence ratings of engineering skills for the ED100 (Korean) and E10 (American) student groups using a 5-option Likert scale (High, Medium High, Neutral, Medium Low, Low). Eight of the ten skills showed statistically significant differences between the two populations. The highest value in each category that has a significant difference is shown in bold. The Spring 2008 and Spring 2009 data from the E10 students were combined. Overall, the E10 students ranked themselves higher than the ED100 students did in six out of ten skills, with five skills showing statistical significance ($p \leq 0.05$).

A closer examination of the results reveals this dichotomy is probably heavily influenced by the academic and cultural backgrounds of each sample. There is a higher percentage of engineering students in the E10 population. Approximately half of the ED100 students will choose non-engineering disciplines, so it is expected that they would be less confident in using "engineering practice" techniques and in understanding the impact of "engineering design and analysis." However, when asked about technical skills, the ED100 students were more confident than the E10 students. They self-rated higher in their ability to "formulate and solve technical problems" and also to "develop designs that meet needs." The lower confidence of ED100 students in their "creativity and practical ingenuity" and stronger confidence in communication skills by students in ED100 is interesting and deserves further study.

5.2.2 Confidence in ABET Skills by Gender

Table 5.3 presents how all students ranked their engineering and design skills by gender, comparing the ED100 men versus E10 men and ED100 women versus E10 women. The numbers in bold represent the highest confidence for each category that was statistically significant. There is a striking similarity in how the American and Korean students rate themselves within each gender category, showing the same patterns of confidence as in Table 5.2. For every category but teamwork and analytical skills, the class would collectively self-report more or less confident. For instance, with "creativity and practical ingenuity", the American students self-rated themselves higher than the Korean students in both the male and female groups.

The most marked differences were in the categories relating to engineering practice and in "creativity and practical ingenuity" – both the E10 men and women self-rated higher than the ED100 men and women ($p \leq 0.05$). These results are consistent with ED100 having a mix of engineering and non-engineering students and therefore less defined engineering skills, as well as the Korean self-perception of being "non-creative." However, the ED100 men self-rated higher in their ability to "identify, form, and solve technical problems". Surprisingly, the ED100 men and women rank themselves higher than the E10 men and women in communication skills. These are the only two categories where the ED100 men rank above the E10 men. The women show more variability, with ED100 women ranking above the E10 women in analytical skills and in their ability to form and solve technical problems, although neither result is statistically significant.

Table 5.4 presents how all students assess their engineering and design skills by class, comparing the ED100 men versus women and E10 men versus women. The bolded numbers represent the highest confidence for each category that was statistically significant.

Table 5.2: Confidence in Engineering Skills by Class
BOLDED numbers represent statistical significance

	Average Confidence ED100	Average Confidence E10	p
Strong analytical skills	3.967	3.978	0.251
Creativity and practical ingenuity	3.46	**3.793**	0.0007
Develop designs that meet needs, constraints, and objectives	**3.569**	3.563	0.0492
Identify, formulate, and solve technical problems	**3.649**	3.474	0.0032
Good communication skills	**3.804**	3.622	0.0017
Good team skills	3.797	**3.963**	0.028
Leadership and management skills	3.633	3.709	0.467
Strong ethics	3.753	**4.192**	0.0008
Use the techniques and tools used in engineering practice	3.265	**3.926**	0.0042
Recognize the global impact of engineering design and analysis	3.188	**3.567**	0.0056

Table 5.3: Confidence in Engineering Skills by Gender
BOLDED numbers represent statistical significance

	Men			**Women**		
	ED100	E10	Δ	ED100	E10	Δ
Strong analytical skills	4.044	4.075	0.031	3.811	3.699	0.112
Creativity and practical ingenuity	3.529	**3.817**	0.288	3.318	**3.723**	0.405
Develop designs that meet needs, constraints, and objectives	3.571	3.579	0.008	3.565	3.518	0.047
Identify, formulate, and solve technical problems	3.755	3.533	0.222	3.432	3.301	0.131
Good communication skills	**3.707**	3.529	0.178	**4**	3.892	0.108
Good team skills	3.725	3.854	0.129	**3.947**	**4.277**	0.33
Leadership and management skills	3.566	3.646	0.08	3.773	3.892	0.119
Strong ethics	3.714	**4.104**	0.39	3.833	**4.446**	0.613
Use the techniques and tools used in engineering practice	3.313	**4.033**	0.72	3.167	**3.614**	0.447
Recognize the global impact of engineering design and analysis	3.165	**3.533**	0.368	3.237	**3.663**	0.426

Table 5.4: Confidence in Engineering Skills by Class and Gender
BOLDED numbers represent statistical significance

	ED100			E10		
	Men	Women	Δ	Men	Women	Δ
Strong analytical skills	**4.044**	3.811	0.233	**4.075**	3.699	0.376
Creativity and practical ingenuity	3.529	3.318	0.211	3.817	3.723	0.094
Develop designs that meet needs, constraints and objectives	3.571	3.565	0.006	3.579	3.518	0.061
Identify, formulate, and solve technical problems	**3.755**	3.432	0.323	**3.533**	3.301	0.232
Good communication skills	3.707	**4**	0.293	3.529	**3.892**	0.363
Good team skills	3.725	**3.947**	0.222	3.854	**4.277**	0.423
Leadership and management skills	3.566	**3.773**	0.207	3.646	**3.892**	0.246
Strong ethics	3.714	3.833	0.119	4.104	**4.446**	0.342
Use the techniques and tools used in engineering practice	3.313	3.167	0.146	**4.033**	3.614	0.419
Recognize the global impact of engineering design and analysis	3.165	3.237	0.072	3.533	3.663	0.13

In spite of the national differences described previously, both populations show similar gender differences. The men ranked higher than the women in their analytical skills, their creativity and practical ingenuity, their ability to identify and solve technical problems, and their ability to use engineering techniques and tools. However, women were more confident in understanding the global impact of engineering design and analysis, and also self-rated higher in their communication skills, team skills, and leadership skills. These patterns highlight the perceived "hard" and "soft" skill sets often attributed to men and women.

5.2.3 Engineering Experience and Culture

In the survey, students were also asked to report what engineering or design related experiences they had prior to entering college. Figure 5.1 presents the data for the E10 (American) and ED100 (Korean) students. No additional details were provided on specific areas within each course. From the results, it appears that many more American students engage in these extracurricular activities than the Korean students. Additionally, the American students seem to have a more dominating presence even in the activities that show significant involvement by Korean students. We note that Korean students' time in the classroom leaves very little opportunity for extracurricular activities and thus their participation is very much tied to curricular activities.

Separately, Korean students reported heavy participation in math and science competitions, which is associated with coursework: 46% and 55%, respectively. We do not have data on how many American students participated in these competitions because those questions were not included in their survey. However, we note that the level of American student participation in computing and art courses is similar to the level of Korean participation in math and science competitions: 45% and 49%, respectively. Thus, this data may reflect differences in the types of opportunities that are available to the students in each country.

This difference in extracurricular activities may explain the students' assessment of their skills. The American students rank higher in "creativity and practical ingenuity" – skills possibly nurtured through artistic endeavors. Conversely, they rate lower in their ability to "identify, formulate and solve technical problems" than the Korean students who focus on early math and science development.

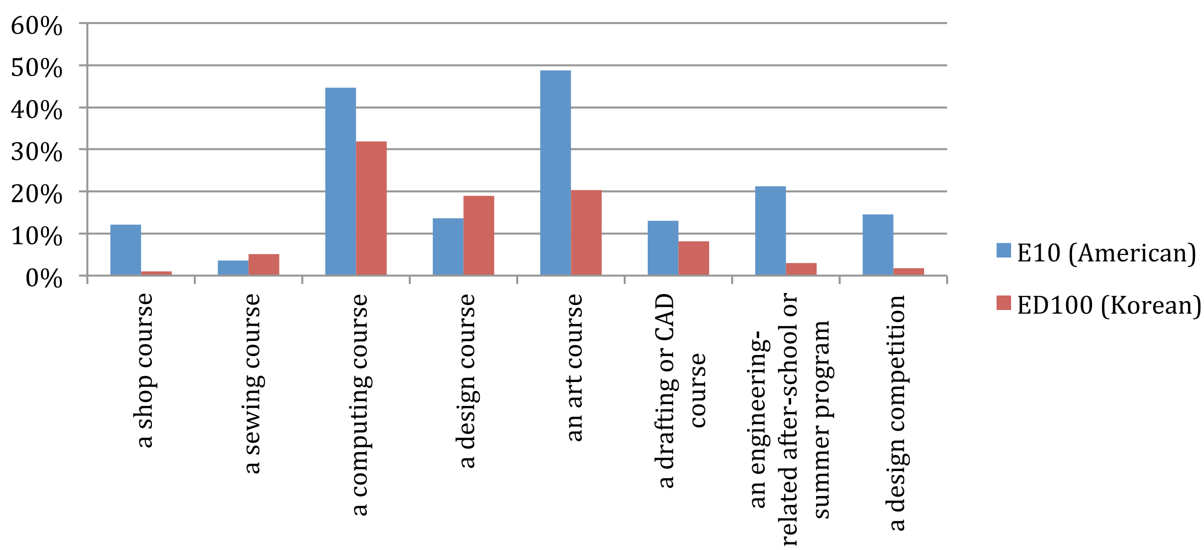

Figure 5.1 Previous Engineering and Design Experiences -

5.2.4 Kolb Learning Styles and Confidence in ABET Skills

Figure 5.2 shows the makeup of learning styles from ED100 and from a population of upper division and graduate students engaged in multidisciplinary design courses at UC Berkeley. Unfortunately, learning style preferences were not originally collected for UC Berkeley students in E10. The literature suggests that learning styles do not change significantly at the college level and thus we do not expect large differences due to a one or two year separation in age.

The breakdown of learning styles is similar between the two national data sets. The largest difference is the percentage of convergers (55% versus 39%) and assimilators (23% and 32%) respectively for the American versus Korean students. Since the difference between convergers and assimilators occurs on the analysis-synthesis axis, the differences in the learning style distributions may be partially explained by the fact that the Korean education system generally emphasizes analysis, sometimes to the exclusion of synthesis. In the ED100 end-of-semester student survey (which was conducted separately from the surveys discussed in this work), 331 out of 413 respondents (80.1%) reported never taking a design class or working on a design project before. Thus, these students may have had little or no opportunity to develop those skills or have their learning style be influenced by them.

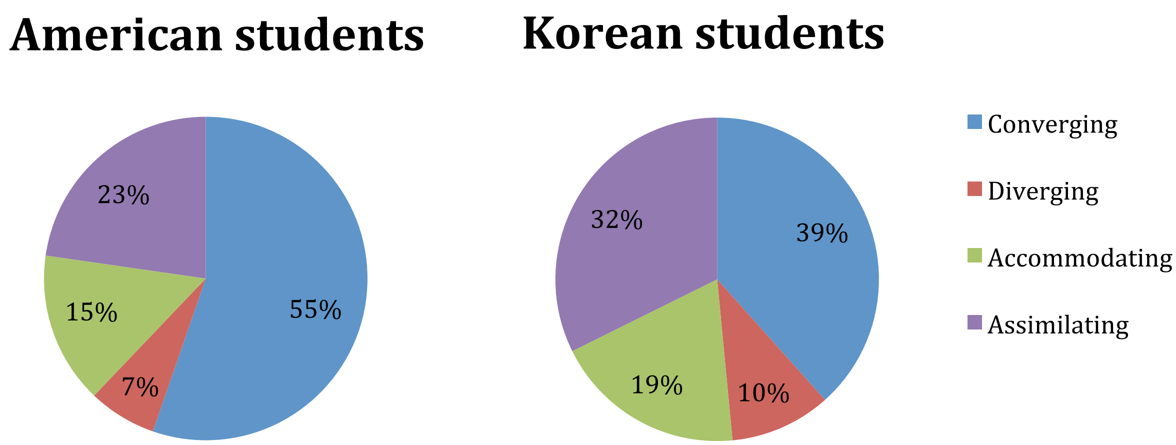

Figure 5.2 Breakdown of Learning Styles

Only the ED100 (Korean) dataset includes the ABET confidence and the Kolb learning style questions in the same sample. Table 5.5 presents the results by learning style for the ED100 (Korean) students in Fall 2010. Learning style data had not been captured for the E10 (American) students and is therefore not included in this table.

These results show the expected behavioral trends for the various learning styles. Accommodators are quick to take initiative and carry out plans, and self-rate themselves higher in leadership and management skills ($p \leq 0.0001$). Convergers, on the other hand, are generally strongest at problem-solving and filtering through many options to set clear objectives. Unsurprisingly, they assess their analytical skills to be the strongest among all other skills. Students with the converging learning style score well in their ability to "analyze and interpret data" ($p=0.001$); data processing is typically associated with assimilating learning style with a very similar high correlation.

There are also unexpected patterns. People who prefer the diverging learning style are typically best at brainstorming and conceiving new ideas. However, this is not reflected in a correlation with "creativity and practical ingenuity" skills, with accommodators ranking highest ($p=0.013$). Divergers have broad, cultural interests and are able to connect needs with the people, but this is not reflected in their confidence in "developing designs that meet needs". The lack of statistical significance may be due, in part, to the relatively small number of students with diverging learning style in the population.

The correlation of positive self-assessment in skills that are typically associated with each learning style validates that learning styles do accurately reflect a person's attributes. It also demonstrates that learning styles do matter in predicting how a person might contribute to the design process. This has strong implications for how to form high-performing design teams: to be most successful in the design process (Figure 1.1), a team should have members with all four learning styles (Figure 1.2). In other words, teams benefit from having the maximum learning style diversity possible.

Table 5.5: Confidence in Engineering Skills by Learning Style
BOLDED numbers represent statistical significance

	Diverging	Converging	Assimilating	Accommodating
Strong analytical skills	3.73	**4.06**	**4.03**	3.77
Creativity and practical ingenuity	3.23	3.49	3.34	**3.68**
Develop designs that meet needs, constraints, and objectives	3.6	3.67	3.46	3.7
Identify, formulate, and solve technical problems	3.53	**3.71**	3.66	3.58
Good communication skills	3.77	**3.96**	3.55	**4.02**
Good team skills	3.73	**3.94**	3.58	**3.86**
Leadership and management skills	3.67	3.75	3.34	**3.91**
Strong ethics	3.6	3.68	3.81	3.61
Design and conduct experiments, and analyze and interpret data	3.47	3.68	3.66	3.25
Use the techniques and tools used in engineering practice	3.33	3.27	3.22	3.19
Recognize the global impact of engineering design and analysis	3.13	3.27	**3.93**	3.46

5.3 Conclusions and Recommendations

This chapter explored the variations in confidence in engineering-related skills among freshman design students in Korea and the United States, under the subtexts of gender and learning style. The students followed a creative, iterative design cycle in their respective courses, resulting in innovative outcomes at the end. The results showed striking differences in confidence levels that may be due to national differences. The American students rated themselves higher in creativity, team skills, ethics, facility with tools of engineering practice, and in recognizing global impact. The Korean students assessed their skills higher in design, problem solving, and communication skills. There were no statistically significant differences in leadership or analytical skills.

Still, we must question whether the national differences may be due, in part, to the difference in disciplinary aspirations in each group. The Korean students were taken from all disciplines as students at KAIST do not declare majors until their sophomore year, whereas most of the American students had already declared engineering as their major. For future research, it would be interesting to perform another analysis with students who have declared their major to identify the contribution of national versus disciplinary differences.

In spite of (what may be) national differences, the students still follow the same gender patterns. The men are more confident in technical and analytical skills, while the women feel stronger in communication and teamwork skills. As such, both cultures may benefit from interventions designed to build confidence in each area, perhaps in the form of continuous feedback on their work – reflecting on what works and amending the mistakes. By providing a forum for students to develop and sharpen their respective skills, they can gain the confidence to successfully face future design challenges and reach the best solutions possible.

Chapter 6

Learning Styles and the Design Process

The previous chapters have presented characterizations to understand the makeup of the design population and data on how designers self-rated themselves in skills that are typically used in the design process, with relation to various diversity factors. This chapter culminates with the examination of the role of diversity in a team actively participating in the design process. I will discuss how diversity factors affect the dynamics and success of a design team, and how we may leverage these factors in design practice. In addition to looking at diversity in learning styles, I also consider other demographic factors, such as discipline and gender.

6.1 Survey Populations and Methods

For this study, data were gathered from students enrolled in "ME290P: Managing the New Product Development Process: Design Theory and Methods", a graduate-level, multidisciplinary design course offered at University of California at Berkeley (UCB). This is a project-based learning class, whereby engineering, business and science students from UCB, along with industrial design students from the California College of Arts (CCA), engage in small design teams to solve a real-world, open-ended design challenge. Over the semester, students learn the tools and techniques of new product development and apply them in their semester-long class projects, while also developing skills important for design and innovation outside the academic environment. This study was performed over two semesters of ME290P, in Fall 2009 (N=70, 16 teams) and in Fall 2010 (N=75, 17 teams). Table 6.1 shows the class breakdown by discipline and gender.

Table 6.1: Class Breakdown by Discipline and Gender

	Male	**Female**	**Total**
Engineering	41	13	54
MBA	33	10	43
Science	11	6	17
Industrial Design	11	8	19
Other	7	5	12
Total	103	42	145

The study was conducted with three surveys during the semester. The first survey was administered at the beginning of the semester and was comprised of two parts: a demographic questionnaire and the Kolb Learning Style Inventory (LSI). This survey served to help students understand their personal styles in observation, framing, solution generation and testing, as well as the preferences of their teammates; the results were intended to drive productive team dynamics and processes from the start of the project.

Midway through the semester, a Peer Review and Team Assessment survey was administered to the class. The purpose of this survey was for students to provide feedback on the current state of their project and team. The questions were divided into seven sections: Goals, Roles, Processes and Procedures, Relationships, Team Effectiveness, Team Performance, and Time Management. The students were also asked to evaluate each teammate on his or her contributions to the team, by dividing up 100 points among all team members, including oneself. These results were presented to the teams and served as a discussion point for making improvements in the remainder of the semester.

The third survey was administered at the end of the semester and was similar to the mid-semester survey with the goal of tracking improvements. The results for Fall 2009 and Fall 2010 were analyzed separately when appropriate because the surveys were worded slightly differently in each year.

6.2 Results and Discussion

6.2.1 Learning Styles of Study Population versus General Population

The distribution of learning styles in our entire study population is shown in Figure 6.1. Overall, the class has a relatively similar learning style breakdown between the Fall 2009 and 2010 groups. The students with converging learning style are most dominant across both semesters. The only difference is the marked absence of divergers in Fall 2010. Students with balanced learning styles are those who have stronger preferences along a single axis, either the Perception (AC+CE) or Processing (AE+RO) Continuum. In the class, twenty-three students demonstrated preferences in the Processing Continuum (AE+RO), for watching and doing, versus four students for the feeling and thinking Perception Continuum (AC+CE).

Table 6.2 shows the scores from each learning style mode (Concrete Experience, Reflective Observation, Abstract Conceptualization, Active Experimentation) for the two classes. The mean values for each mode are relatively close and within 2 points of one another, but the range of individual scores is wide (nearly 30 point differential for every mode). This distribution is similar to that reported for research universities in the Kolb manual on LSI.

In this study group, the converging learning style is most dominant (Table 6.3). This is not surprising given the proportion of engineers and business students in the class. However, there is a significant paucity of divergers, except among the Industrial Design students. “Other” represents the Science and Humanities fields, such as Genetics and Plant Biology, Art History, and Information Science.

When comparing learning styles by gender, women and men typically demonstrate different learning style preferences. In particular, men score higher on the Abstract Conceptualization spectrum and fit well with the Assimilating or Converging styles. On the other hand, women prefer practical, hands-on environments with either Diverging or Accommodating learning styles.

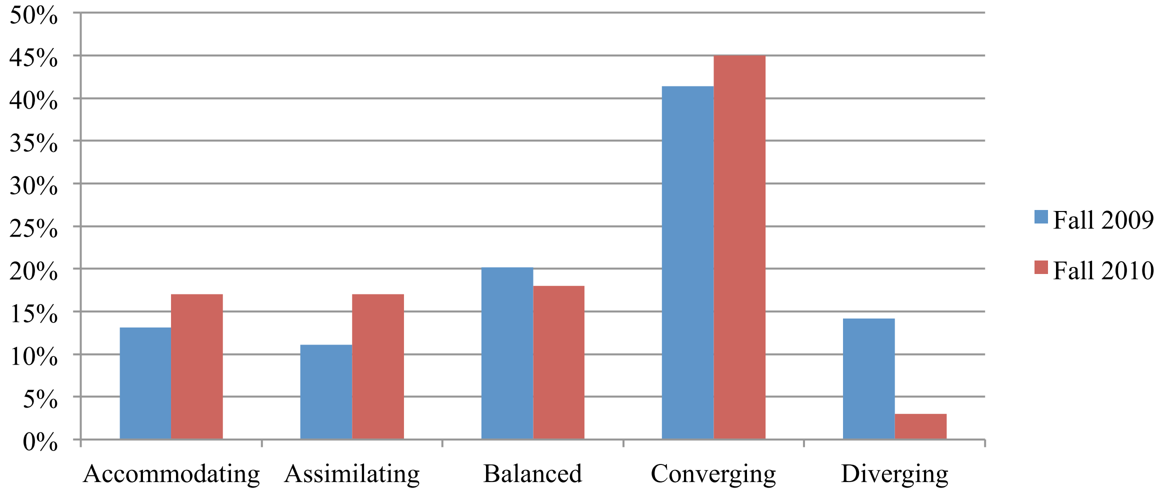

Figure 6.1 Learning Styles of Design Students

Table 6.2: Learning Style Scores

	CE	RO	AC	AE	
Fall 2010	25.5	26.2	34.1	34.2	Mean
	6.3	6.9	6.6	6.3	Std Dev
	15-39	13-41	20-46	21-47	Range
Fall 2009	26.1	28.2	32.4	33.2	Mean
	6.6	7.0	7.1	7.5	Std Dev
	15-44	15-41	14-46	17-47	Range

Table 6.3: Learning Styles by Discipline

	Engineering	Business	Industrial Design	Other	**Total**
Accommodating	5 (9%)	9 (21%)	4 (21%)	4 (14%)	**22**
Assimilating	9 (17%)	3 (7%)	4 (21%)	5 (17%)	**21**
Balanced	10 (19%)	9 (21%)	3 (16%)	5 (17%)	**27**
Converging	27 (50%)	19 (44%)	5 (26%)	12 (41%)	**63**
Diverging	3 (6%)	3 (7%)	3 (16%)	3 (10%)	**12**
Total	**54**	**43**	**19**	**29**	**145**

6.2.2 Learning Style Profiles of Teams

To analyze learning styles on the project team level, we identified each team's overall learning profile by averaging the team members' individual scores on the four stages of learning (CE, RO, AC, AE). Figure 6.2 illustrates the learning style profiles of two distinct teams and of the class average. Team 1 represents the team with the most diverging learning style in the class and Team 2 represents the team with the most converging learning style in the class.

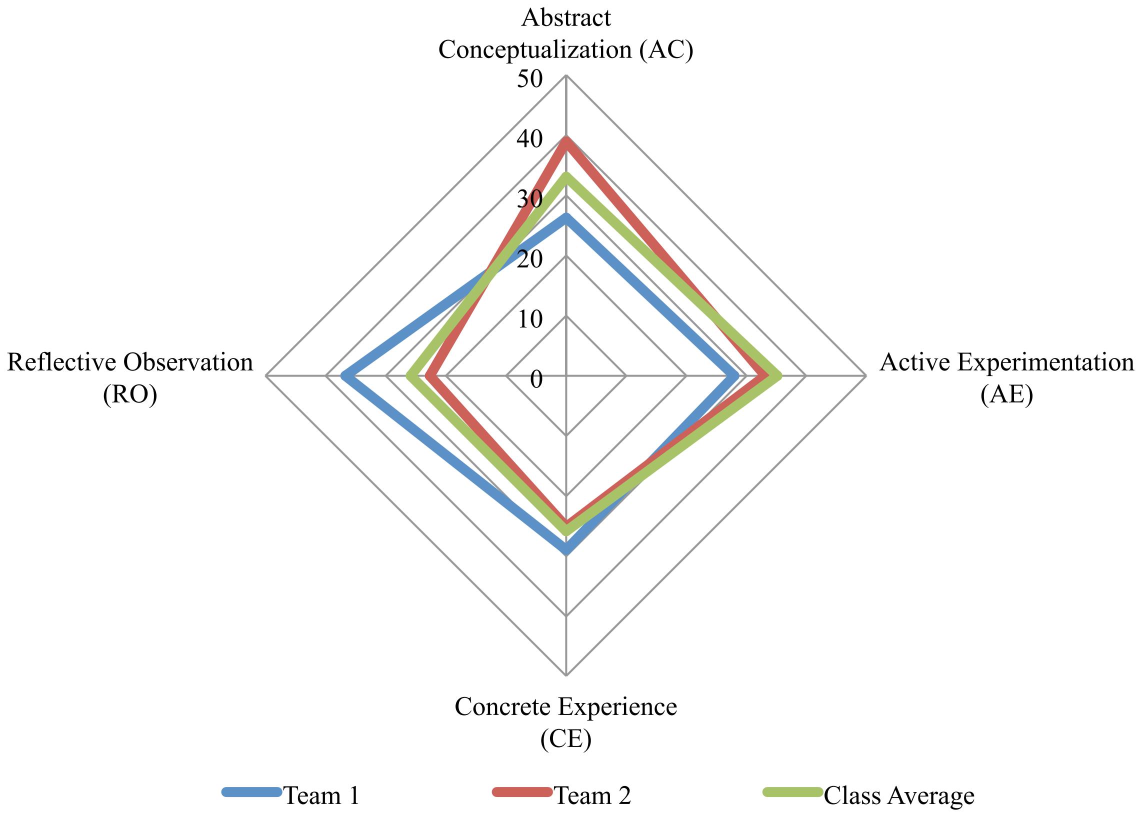

Figure 6.2 Learning Style Profiles of Teams

Each polygon represents one team's learning style profile. The points at which the polygons intersect with each axis represent the team's average score in that respective continuum. The longer lines demonstrate greater strengths in their respective quadrants. We can observe that Team 1 has greater scores in the RO and CE dimensions, representing its more dominant Diverging learning style, while Team 2 has greater scores in the AC and AE dimensions of the "Converging" region. The Class Average falls between these two profiles and shows a stronger preference for converging.

6.2.3 Learning Styles and Team Assessment Results

With these aggregated learning style profiles, how design teams rated themselves on the mid-semester surveys was then examined to understand team coherence and performance. Design teams are compared with respect to the level of converging learning style within the teams because of the converging dominance in the class. Tables 6.4 and 6.5 show the results of the mid-semester survey, evaluated by how many convergers were on a team. This was done for Fall 2009 and Fall 2010 classes respectively.

The bolded numbers represent the results that are statistically significant ($p<0.05$). Each column represents a different group of teams, which are clustered by the number of convergers in the team. The symbols (*, †, and ∂) identify the pair of groups in each row between which a statistically significant difference was found. For example, in response to Question 1: "As a team, we are clear about our purpose", the teams with one converger scored significantly higher (4.25) in contrast with teams with three convergers (3.7). The results were not statistically significant between the other populations. In Question 8: "The team enjoys working together", the score attained by teams with one converger (4.56) was significantly larger than both the score of the team with two convergers (4.13) and the score of the team with three convergers (3.91). The results from Fall 2009 were normalized to a 5-point scale.

The most striking observation here is that the ratings significantly decrease as the number of convergers on the team increases, specifically from one to four convergers. This seems to imply that the converging learners do affect design teams, with fewer convergers providing greater benefit. Indeed, converging learners are valuable to design teams – they can find practical uses for ideas and enjoy experimenting with new ideas. However, they also prefer to internalize their theories before acting. Perhaps an entire team of persistent thinkers translates to little or no dialogue between the team, and limited or slower success.

Many of the questions showing statistically significant results pertain to working as a team. Of these, the most direct statement about team interactions: "The team enjoys working together", shows teams with one converger rating highest of all. One might have expected a more diverse team, particularly one comprised of different learning styles, to clash with one another; however, here the more homogeneous teams, with respect to converging learning styles, report more tension. This may also be indicative of how teams spend their time together. In questions relating to productivity (Q7, Q10, Q16), teams with one converger report making the best use of time. This could be because teams with multiple convergers were so alike that team members were complacent with one another, resulting in a lack of design momentum; or they may have experienced greater conflict because of strong, similar personalities, and squandered time arguing over simple ideas and tasks. More broadly, the teams with one converging learner believe themselves to be the highest-performing teams (Q12) and with the highest quality outputs (Q11), rating nearly one point above teams with four converging learners.

Interestingly, when the teams were asked about innovation: "Our team is innovative", no group showed statistically significant different results. So although teams with one converging learner believe they are most high-performing and productive of all teams, they do not necessarily believe they are any more innovative.

The leading question is thus how the learning style profiles compare between the different teams, with respect to the number of convergers, and whether these perceptions are actually mirrored in the team deliverables.

Table 6.4: Mid-Semester Assessment Results, by # Convergers on Team (Fall 2009)

		1 converger	2 convergers	3 convergers	4 convergers
1	As a team, we are clear about our purpose.	**4.25***	4.20	**3.70***	3.61
2	The team is successfully achieving project goals to date.	**4.37***	**3.72***	4.22	3.83
3	The team is committed to learning about the tools, techniques and process taught in this class.	4.13	**3.93***	**4.43***	3.89
4	The members of my team have a shared understanding of the roles and responsibilities played by individuals on the team.	**3.65***	3.63	3.70	**3.19***
5	All members of the team have shared equitably in the tasks performed to date.	**3.73***	**3.83**†	3.70	**2.64***†
6	We have two-way communication with our speakers/design coaches.	**4.05***	**3.97**†	3.65	**2.78***†
7	We spend sufficient time making sure the team is working on what we are supposed to be doing.	**4.05***	3.60	3.83	**3.19***
8	The team enjoys working together.	**4.56***†	**4.13***	**3.91**†	4.03
9	As a team, we are accomplishing what we have set out to accomplish.	**4.21***	3.93	**3.70***	3.61
10	The time we spend together as a team is productive.	**4.52***†	**3.93***	**4.06**†	3.75
11	What we produce as a team are high-quality outputs.	**4.40***†∂	**3.97***	**3.80**†	**3.47**∂
12	Overall, we are a high-performing team.	**4.29***†	**3.80***	**3.59**†	3.47

Table 6.5: Mid-Semester Assessment Results, by # Convergers on Team (Fall 2010)

		1 converger	2 convergers	4 convergers
13	We have discussed our individual learning goals for the class and the project with each other.	**4.41***†	**3.90***	**3.75**†
14	We have agendas for our team meetings.	**4.45***†	**3.67***	**3.44**†
15	We have the skills and experience on the team that we need to be successful.	**4.45***	**4.07***	4.00
16	Our team meetings are productive.	**4.45***	4.27	**3.81***
17	I am learning valuable lessons about my own leadership by being on this team.	**4.41***	4.13	**3.81***

Table 6.6: Average Learning Style Profiles of Entire Team, by # Convergers

Learning Styles of Entire Team	Abstract Conceptualization	Active Experience	Concrete Experience	Reflective Observation
Teams with 1 Converger (T1)	32.1	34.0	26.0	27.8
Teams with 2 Convergers (T2)	33.1	33.9	26.4	26.5
Teams with 3 Convergers (T3)	33.1	35.5	25.7	25.7
Teams with 4 Convergers (T4)	36.5	35.2	25.0	23.3

Table 6.7: Overall Project Score of Teams, by # Convergers

Overall Score	# Convergers	Learning Style Breakdown	Male	Female	Team
4.26	1	1 Accom, 2 Assim, 1 Con	1	3	2010-3
4.10	1	2 Accom, 2 Bal, 1 Con	2	3	2010-13
4.08	1	1 Con, 1 Assim, 1 Bal	2	1	2009-9
4.07	2	1 Accom, 1 Bal, 2 Con	2	2	2010-11
4.02	4	1 Assim, 4 Con	4	1	2010-1
4.01	1	1 Accom, 1 Con, 1 Bal	2	1	2009-5
3.95	1	1 Accom, 2 Div, 1 Bal, 1 Con	2	3	2009-3
3.94	1	2 Assim, 1 Bal, 1 Con	3	1	2010-15
3.92	4	1 Assim, 1 Bal, 4 Con	6	0	2010-14
3.92	2	1 Bal, 2 Con	3	0	2010-2
3.90	3	3 Con, 1 Assim, 1 Div	2	3	2009-8
3.90	2	2 Assim, 1 Bal, 1 Accom, 2 Con	0	6	2009-15
3.90	2	2 Con, 2 Div, 1 Accom, 1 Bal	1	5	2009-13
3.86	1	1 Bal, 1 Accom, 1 Con	0	3	2009-10
3.86	4	1 Assim, 4 Con	5	0	2010-12
3.85	2	2 Con, 1 Div	2	1	2009-12
3.84	1	1 Con, 1 Accom, 1 Bal	1	2	2009-16
3.83	0	2 Bal	0	2	2009-7
3.81	2	3 Assim, 2 Con	2	3	2010-17
3.75	2	3 Accom, 2 Con	4	1	2010-9
3.74	2	2 Bal, 2 Con, 1 Div, 1 Accom	1	5	2009-6
3.73	3	1 Div, 1 Accom, 3 Con, 1 Bal	3	3	2009-1
3.63	2	2 Con, 1 Assim, 1 Div	1	3	2009-14
3.53	1	1 Accom, 1 Assim, 2 Bal, 1 Con	4	1	2010-5
3.53	2	1 Accom, 1 Assim, 2 Con	1	3	2010-4
3.53	3	3 Con, 1 Bal, 1 Assim	0	5	2009-11
3.50	4	4 Con, 1 Div, 1 Accom	1	4	2009-2
3.50	3	1 Accom, 3 Con	3	1	2010-16
3.42	2	3 Bal, 2 Con	4	1	2010-10
3.40	1	2 Assim, 1 Bal, 1 Con	0	5	2009-4
3.29	2	1 Accom, 1 Bal, 2 Con	4	0	2010-6
3.07	0	1 Assim, 1 Bal, 1 Div	0	3	2010-7
3.01	1	2 Accom, 1 Con, 1 Div	3	1	2010-8

6.2.4 Learning Styles and Team Performance Results

Table 6.6 presents the average learning style profiles of the entire team, clustered by the number of convergers on each team. Recall that the converging learning style is defined by the Abstract Conceptualization + Active Experimentation combination and was the predominant learning style in our sample. As expected, we see that the scores for AC and AE rise and the scores for CE and RO fall for the team as the number of convergers increases.

It can be observed that the T1 and T2 teams have remarkably similar team profiles (within 1 point), yet T2 teams rate themselves lower than T1 teams in all but one question of the mid-semester team and peer assessments. This implies that it is not just the learning profile of the converging learner that matters to a team, but the number of convergers on the team. Ultimately, the team benefits from a very strong converging team member, but may need equally strong non-converging teammates to balance the entire team out.

Table 6.7 shows the team's actual project score by external reviewers and faculty at the end of the semester. These external reviewers included design industry judges, who ranked projects according to the quality of their mission statement, customer/user needs, concept generation, concept selection, prototype, and business analysis. This ranking is taken as a proxy for greater innovation and overall success. The table also includes the number of convergers in the team, the team composition in regards to learning styles, and gender.

It can be noted that of the eleven teams with only one converger, six appear at the top of the list of highest performing teams, and the highest performing teams demonstrate gender diversity. Conversely, the lowest performing teams lacked gender diversity; three of the bottom four teams were either all male or all female. Although the lowest performing team had one woman and three men, the team was clearly dominated by the male students; the female was a shy CCA undergraduate student and a non-native English speaker. There is no pattern that appears among teams with 2, 3, and 4 convergers; rather, they are sprinkled through the grade distribution.

Grades were also compared with the midterm evaluation scores to uncover any specific correlations between how a team perceived itself and how they actually performed at the end of the semester. The results show little correlation between the mid-semester team self-assessments and their actual project performance when measured with the entire class, with the highest r-value at 0.30. The instructors speculate that their interventions may have been effective overall – extreme problems were addressed and corrective action taken. Student feedback at the end of the semester praised the value of the teamwork skills developed in the class.

An analysis of end-of-semester evaluation scores and project grades did yield significant correlation coefficients and many of the values were much higher, indicative that the final team self-assessment was correlated with final grades. For example, when the teams are compared by the number of convergers with their final team grades, some interesting relationships are revealed. Figure 6.3 shows a high, statistically significant correlation between how productive teams with one converger believe their meetings to be and their final project grade.

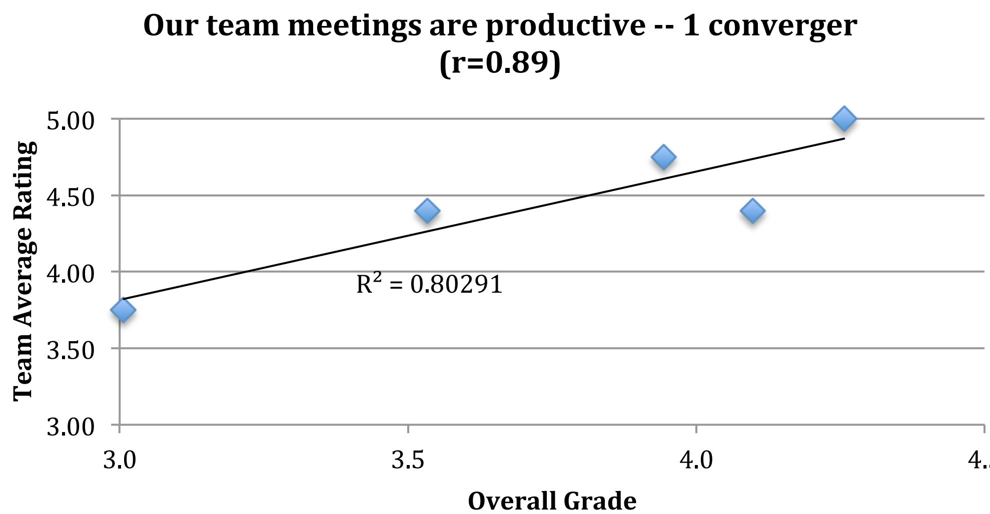

Figure 6.3 Mid-Semester Evaluations versus Overall Project Score

6.2.5 Learning Styles and Mid- and End-of-Semester Analysis

Table 6.8 presents the comparison of results from the midterm and end-of-semester surveys, for Fall 2009. Overall, the post-semester scores are higher with the ones in bold being statistically significant. Here, Converging and Balanced students show the most significant perception of team improvements. This is a favorable result, as it indicates the students are likely becoming more comfortable with themselves, their team, and project over time, or that the teaching staff interventions were successful in dissipating team conflict, or both.

Table 6.8: Mid- and End-of-Semester Team Evaluations

		Accommodating		Balanced		Converging	
		Pre	Post	Pre	Post	Pre	Post
1	As a team, we are clear about our purpose.	4.38	4.58	4.47	4.85	**3.87***	**4.30***
2	As a team, we are clear about our shared values.	4.17	4.38	**4.09***	**4.55***	3.70	3.90
3	The team is committed to learning about the tools, techniques and process taught in this class.	4.27	4.48	**3.86***	**4.62***	4.20	4.33
4	The members of my team have a shared understanding of the roles and responsibilities played by individuals on the team.	3.33	3.96	**3.94***	**4.47***	**3.47**†	**4.07**†
5	As a team, we are accomplishing what we have set out to accomplish.	**3.96***	**4.69***	4.24	4.62	**3.87**†	**4.47**†
6	What we produce as a team are high-quality outputs.	4.27	4.58	**4.09***	**4.62***	4.00	4.30
7	We are taking advantage of the specific areas of expertise of the individual members of the team.	3.44	4.27	4.24	4.50	**3.88***	**4.37***

6.3 Conclusions and Recommendations

In this chapter, the Kolb learning styles of students in a graduate-level design course were explored over two semesters. It was found that the students in this course were most dominant in the converging learning style, and most lacking in the diverging learning style. It was also found that design teams with just one converger generally performed better in their self-perception of team performance than teams with multiple convergers, at least before substantial instructor intervention. There was some indication that teams with a single converger dominated the highest performing teams judged at the end of the semester by external reviewers. As all of the teams had diversity in learning styles, except those over-dominated by convergers, it is not possible to draw any other conclusions on the benefits of diversity in learning styles.

It can be noted that the lowest performing teams lacked gender diversity, as opposed to the teams at the top of the rating list with stronger gender diversity. This result could be a consequence of gender differences in learning styles or personality types. The results were only suggestive, but are strong enough to motivate further research into this intersection of cognitive styles and gender on design teams.

It was also found that a mid-term evaluation of perceived team performance with effective instructor intervention increased the team perception of their final performance at the end of the semester. This was further validated from positive teacher evaluations on teamwork instruction and interventions.

These results provide support for recommending diverse representation among design teams. Teams that do not have such diversity may benefit from interventions that encourage teams to think outside their comfort zones and to assume different roles amongst themselves to help spur more meaningful progress and productive teamwork. Ultimately, understanding and utilizing the different learning styles will benefit design teams and enable members to perform at their best levels.

Chapter 7

Conclusions

Learning styles are particularly important in innovation research because of their connection to the design process, yet there has not been any significant prior study in this area. This poses a great opportunity for both understanding and leveraging diversity in design and it is this gap that this research fills. My main contributions are to:

1. Characterize a relevant range of innovation-oriented populations
2. Study the effects of learning style diversity within teams actively engaged in design and innovation

To accomplish these two goals, I collected data on learning style diversity, along with other demographic data, from various academic and industry populations engaged in the design process (Table 3.1). For some groups, I also collected information about their experiences in the design process and of their design outcomes. This research database gave me a window into the diversity makeup of the different groups and how it affected their design experiences. The database of learning styles and gender was collected from 6,686 subjects, the largest study ever since Kolb's original research.

Table 3.1: Summary of data collected (from Chapter 3)

	Learning Style	Gender	UG Major	Ethnicity	Job Level	Company	MBTI type
Academic	4616	4616	3467	2085	1950	1836	1138
Corporate	2070	2070	374	785	1503	1732	0
Grand Total	**6686**	**6686**	**3841**	**2870**	**3453**	**3568**	**1138**

The findings from characterizing the design population were surprising and intriguing. Across the entire population of students and professionals, across all levels and ages, the converging learning style dominated and there was a significant lack of diverging learners. This is particularly interesting because the qualities of diverging learners are particularly beneficial to design and innovation. They are described as open-minded, empathetic, and sensitive to others needs, which helps them to understand the end user and to reflect this in a product or system. Yet, they were largely absent from this innovation-geared population. In fact, a balance of all four learning styles is the expected breakdown, based on Kolb's original classification scheme. Instead, all populations I studied showed the converging learning style as the dominant preference.

When compared across gender, statistically significant differences were found across learning styles when the population studies are viewed as a whole. This perhaps underlines differences, on average, between men and women, in how they approach problems, in how they relate to people, in how they capture information. A closer examination of disciplines, however, reveals more nuanced findings, where gender matters for learning styles among business people but not among engineers. The implications of whether learning styles do or do not matter in certain scenarios raise interesting questions in how to best leverage this diversity between men and women.

I also explored international populations engaged in design. Freshman design students in Korea and the United States showed striking differences in confidence in engineering-related skills: American students rating higher in creativity, team skills, ethics, facility with tools of engineering practice, and in recognizing global impact, and Korean students assessed their skills higher in design, problem solving, and communication skills. However, the students followed the same gender patterns: men are more confident in technical and analytical skills and women feel stronger in communication and teamwork skills.

Finally, I examined how learning style diversity actually affected design team outcomes and found that design teams with just one team member with the converging learning style generally performed better than teams with multiple team members with converging learning style. The lowest performing teams also lacked gender diversity in the groups I studied. My hypothesis was that design teams will have the most success when comprised of members who actively think outside the box, from different perspectives, and support multiple approaches to a problem. My research supports this hypotheses, but more research is needed.

Future Research

This research leads to interesting follow up questions.

The foremost question is where are all the diverging learners in the innovation-oriented population? Although more prevalent in service occupations such as health care, are there other populations in design and innovation where divergers exist in larger numbers? Perhaps in firms that specialize in empathic design and design research? It seems that the number of diverging learners and more balanced learners should at least counter that of strongly converging learners, yet they are mostly absent in the populations I studied.

Relatedly, the extreme dominance of converging learning style raises the question of how design teams would perform if other learning styles were better represented. Due to the large number of convergers and the scarcity of divergers in my populations, I was not able to conduct broader outcome studies of team cognitive diversity based on learning styles. It has been shown that each learning style connects well with a different step of the design process; how much better or quicker could design and innovation be achieved when converging learners do not dominate? What patterns might emerge from studying teams with greater diversity of learning styles?

One fascinating result was the finding that female engineering students had similar learning style preferences as male engineering students, yet in other populations there were significant differences. Is this a results of self-selection in which a narrow segment of the female population go into engineering, and that they are more likely to be convergers or assimilators. Certainly the messages given about engineering careers emphasize mathematics over empathy and the admissions process is biased towards convergers as well, regardless of gender. Or do female students come in with more diversity, but get socialized into the dominant form?

Another area of research would be to compare my results with Kolb learning style diversity, with diversity of other metrics of cognitive diversity, such as the Adaption-Innovation Inventory (ref).

Finally, these results show that people engaged in design do not have the same learning styles as people in the general population. It would be interesting to explore why this is, perhaps due to the demands of the design world, or from educational influence, or because of another reason altogether.

Ultimately, diversity and teaming are required to successfully innovate during design processes. It is important to continue exploring how to leverage this diversity to achieve design and innovation.

Bibliography

1. ABEEK, A. C. (n.d.). Retrieved 2011, from http://www.abeek.or.kr/htmls_kr/en/index.jsp:

2. ABET. (n.d.). *Criteria for Accrediting Engineering Programs*. Retrieved January 20, 2011, from http://abet.org/: http://abet.org

3. Adrian, F. (1992). Personality and Learning Style: A Study of Three Instruments. *Personality and Individual Differences* , 13, No. 4, 429-438.

4. Allinson, C. W., & Hayes, J. (1988). The Learning Styles Questionnaire: An Alernative to Kolb's Inventory. *Journal of Management Studies* , 25, No. 3, 269-281.

5. Allinson, C. W., & Hayes, J. (1990). Validity of the Learning Styles Questionnaire. *Psychological Reports* , 67, No. 3, 859-866.

6. Ancona, D. G., & Caldwell, D. (2007). Improving the Performance of New Product Teams. *Research-Technology Management* , 50, No. 5, 37-43.

7. Ancona, D. G., & Caldwell, D. F. (1992). Demography and Design: Predictors of New Product Team Performance. *Organization Science* , 3, No. 3, 321-341.

8. Barton Jr., W. A. (1926). The Effect of Group Activity and Individual Effort in Developing Ability to Solve Problems in First-year Algebra. *Journal of Educational Administration and Supervision* , 12, 512-518.

9. Beaty, W. E., & Shaw, M. E. (1965). Some effects of social interaction on probability learning. *Journal of Psychology* , 59, 299-306.

10. Beckman, S. L., & Barry, M. (2007). Innovation as a Learning Process: Embedding Design Thinking. *Harvard Business Review* .

11. Bell, S. T. (2007). Deep-Level Composition Variables As Predictors of Team Performance: A Meta-Analysis. *Journal of Applied Psychology* , 92, 595-615.

12. Bell, S. T., Villado, A. J., Lukasik, M. A., Belau, L., & Briggs, A. L. (2011). Getting Specific About Demographic Diversity Variable and Team Performance Relationships: A Meta-Analysis. *Journal of Management* , 37, 709.

13. Bereiter, C., & Scardamalia, M. (1993). Surpassing Ourselves: An Inquiry into the Nature and Implications of Expertise. Open Court Publishing Company.

14. Block, J. (1995). A Contrarian View of the Five-Factor Approach to Personality Description. *Psychological Bulletin* , 117, No. 2, 187-215.

15. Bonner, J. M., Ruekert, R. W., & Walker, O. C. (2002). Upper Management Control of New Product Development Projects and Project Performance. *Journal of Product Innovation Management* , 19, No. 3, 233-245.

16. Bowers, C. A. (2000). When Member Homogeneity is Needed in Work Teams: A Meta-Analysis. *Small Group Research , 31*, 305-307.

17. Bradley, J. H., & Hebert, F. J. (1997). The Effect of Personality Type on Team Performance. *Journal of Management Development* , 16, No. 5, 337-353.

18. Brewer, M. B. (1979). In-Group Bias in the Minimal Intergroup Situation: A Cognitive-Motivational Analysis. *Psychological Bulletin* , 86, 307-324.

19. Brown, S. L., & Eisenhardt, K. M. (1995). Product Development: Past Research, Present Findings, and Future Directions. *The Academy of Management Review* , 20, No. 2, 343-378.

20. Bunderson, J. S., & Sutcliffe, K. (2002). Comparing Alternative Conceptualizations of Functional Diversity in Management Teams: Process and Performance Effects. *The Academy of Management Journal* , 45, No. 5, 875-893.

21. Byrne, D. E. (1971). An Overview (and Underview) of Research and Theory within the Attraction Paradigm. *Journal of Social and Personal Relationships* , 14, No. 3, 417-431.

22. Cady, S. H., & Valentine, J. (1999). Team Innovation and Perceptions of Consideration: What Difference Does Diversity Make? *Small Group Research* , 30, No. 6, 730-750.

23. Callaghan, E. (2009). Personalities of Design Thinking. *Design Management Journal* , 4, No. 1, 20-32.

24. Carbonell, P., & Rodriguez, A. I. (2006). Designing Teams for Speedy Product Development: The Moderating Effect of Technological Complexity. *Journal of Business Research* , 59, No. 2, 225-232.

25. Carrizosa, K., & Sheppard, S. (2000). The Importance of Learning Styles in Group Design Work. *30th ASEE/IEEE Frontiers in Education Conference T2B-12*, (pp. 1-6). Kansas City, MO.

26. Cassidy, S. (2004). Learning Styles: An Overview of Theories, Models, and Measures. *Educational Psychology* , 24, No. 4, 419-444.

27. Castro, O., & Peck, V. (2005). Learning Styles and Foreign Language Learning Difficulties. *Foreign Language Annals* , 38, No. 3, 401-409.
28. Cavanagh, S. J., Hogan, K., & Ramgopal, T. (1995). The Assessment of Student Nurse Learning Styles Using the Kolb Learning Styles Inventory. *Nurse Education Today* , 15, No. 3, 177-183.
29. Chang, S. (2004). Science and Engineering Education in Korea: Educating the Engineer for the 21st Century. *Workshop on Global Engineering Education*, (pp. 91-96).
30. Chen, C.-J. (2007). Information Technology, Organizational Structure, and New Product Development - The Mediating Effect of Cross-Functional Team Interaction. *Engineering Management, IEEE Transactions* , 54, No. 4, 687-698.
31. Cohen, S. G., & Bailey, D. E. (1997). What Makes Team Work: Group Effectiveness Research from the Shop Floor to the Executive Suite. *Journal of Management , 23* (3), 239-290.
32. Curnow, R., & Moring, G. (1968). ‘Project sappho’: A study in industrial innovation . *Futures , 1* (2), 82-90.
33. D'Amore, A., James, S., & Mitchell, E. K. (2012). Learning Styles of First-Year Undergraduate Nursing and Midwifery Students: A Cross-Sectional Survey Utilising the Kolb Learning Style Inventory. *Nurse Education Today* , 32, No. 5, 506-515.
34. Danneels, E., & Sethi, R. (2003). Antecedents of New Product Program Creativity: The Moderating Role of Environmental Turbulence. *Academy of Management*, (pp. A1-A6). Seattle, WA.
35. Deeter-Schmelz, D. R., & Kennedy, K. N. (2002). Enriching Our Understanding of Student Team Effectiveness. *Journal of Marketing Education , 24* (2), 114-124.
36. Devine, D. J., Clayton, L. D., Philips, J. L., Dunford, B. B., & Melner, S. B. (1999). Teams in Organizations: Prevalence, Characteristics, and Effectiveness. *Small Group Research , 30* (6), 678-711. .
37. Diaz, D. P., & Cartnal, R. B. (1999). Students' Learning Styles in Two Classes: Online Distance Learning and Equivalent On-Campus. *College Teaching* , 47, No. 4, 130-155.
38. Digman, J. (1990). Personality Structure: Emergence of the Five-Factor Model. *Annual Review of Psychology , 41*, 417-440.
39. Donovan, M. S., Bransford, J. D., & Pellegrino, J. W. (2000). *How People Learn: Brain, Mind, Experience, and School.* Washington, DC: National Academy Press.
40. Dunn, R., DeBello, T., Brennan, P., Krimsky, J., & Murrain, P. (1981). Learning Style Researchers Define Differences Differently. *Educational Leadership* , 38, No. 5, 372-75.
41. Edmondson, A. C. (2012). *Teaming: How Organizations Learn, Innovate, and Compete in the Knowledge Economy.* San Francisco, CA: John Wiley & Sons, Inc.
42. Ely, R. J., & Thomas, D. A. (2001). Cultural Diversity at Work: The Effects of Diversity Perspectives on Work Group Processes and Outcomes. *Administrative Science Quarterly , 46* (2), 229-273.
43. Engels, P. T., & de Gara, C. (2010). Learning Styles of medical students, general surgery residents, and general surgeons: implications for surgical education. *BMC Medical Education , 10*, 51.
44. Federico, P. A. (2000). Learning Styles and Student Attitudes Toward Various Aspects of Network-Based Instruction. *Computers in Human Behavior* , 16, No. 4, 359-379.
45. Felder, R. M., & Silverman, L. K. (1988). Learning and Teaching Styles in Engineering Education. *Engineering Education* , 78, No. 7, 674-681.
46. Fisher, R. J., Maltz, E., & Jaworski, B. J. (1997). Enhancing Communication Between Marketing and Engineering: The Moderating Role of Relative Functional Identification. *Journal of Marketing* , 61, No. 3, 54-70.
47. Fox, J., & Bartholomae, S. (1999). Student learning style and educational outcomes: evidence from a family financial management course. *Financial Services Review , 8*, 235-251.
48. Freedman, R. D., & Stumpf, S. A. (1978). What Can One Learn from the Learning Style Inventory? *Academy of Management Journal* , 21, No. 2, 275-282.
49. Freedman, R. D., & Stumpf, S. A. (1980). Learning Style Theory: Less Than Meets the Eye. *The Academy of Management Review* , 5, No. 3, 445-447.
50. Froehle, C. M., Roth, A. V., Chase, R. B., & Voss, C. A. (2000). Antecedents of New Service Development Effectiveness: An Exploratory Examination of Strategic Operations Choices. *Journal of Service Research* , 3, 3.
51. Furnham, A. (1992). Personality and Learning Style: A Study of Three Instruments. *Personality and Individual Differences* , 13, No. 4, 429-438.
52. Grasha, A. F. (1996). *Teaching With Style: The Integration of Teaching and Learning Styles in the Classroom*. From The Professional & Organizational Development Network in Higher Education: www.podnetwork.org

53. Harrison, D. A., & Klein, K. J. (2007). What's the Difference? Diversity Constructs as Separation, Variety, or Disparity in Organizations. *Academy of Management Review* , 32, 1199-1228.
54. Hitt, M. A., Nixon, R. D., Hoskisson, R. E., & Kochher, R. (1999). *Corporate Entrepreneurship and Cross-Functional Fertilization: Activation, Process, and Disintegration of a New Product Design Team.* College Station, Texas: Mays Business School, Texas A&M University.
55. Hoegl, M., Ernst, H., & Proserpio, L. (2007). How Teamwork Matters More as Team Member Dispersion Increases. *Journal of Product Innovation Management* , 24, No. 2, 156-165.
56. Hoevemeyer, V. A. (1993). How Effective Is Your Team? *Training and Develoment* , 47, No. 9, 67-71.
57. Homan, A. C., Hollenbeck, J. R., Humphrey, S., Van Knippenberg, D., Ilgen, D. R., & Van Kleef, G. A. (2008). Facing Differences with an Open Mind: Openness to Experience, Salience of Intragroup Differences, and Performance of Diverse Work Groups. *Academy of Management Journal* , 51, 1204-1222.
58. Horwitz, S. K. (2007). The Effects of Team Diversity on Team Outcomes: A Meta-Analytic Review of Team Demography. *Journal of Management , 33* (6), 987-1015.
59. Howell, J. M., & Shea, C. M. (2006). Effects of Champion Behavior, Team Potemcy, and External Communication Activities on Predicting Team Performance. *Group Organization Management , 31* (2), 180-211.
60. Jackson, S. E., Joshi, A., & Erhardt, N. L. (2003). Recent Research on Team and Organizational Diversity: SWOT Analysis and Implications. *Journal of Management* , 29, 801-830.
61. Janssen, O., & Huang, X. (2008). Us and Me: Team Identification ad Individual Differentation as Complementary Drivers of Team Members' Citizenship and Creative Behaviors. *Journal of Management , 34* (1), 69-88.
62. Jassawalla, A. R., & Sashittal, H. C. (2000). Strategies of Effective New Product Team Leaders. *California Management Review* , 42, No. 2, 35.
63. Jehn, K. E., Northcraft, G. B., & Neale, M. A. (1999). Why Differences Make a Difference: A Field Study of Diversity, Conflict, and Performance in Workgroups. *Administrative Science Quarterly* , 44, 741-763.
64. Jonassen, D. H., & Grabowski, B. L. (1993). *Handbook of Individual Differences, Learning & Instruction.* New York: Routledge.
65. Joshi, A. A., & Roh, H. (2009). The Role of Context in Work Team Diversity Research: A Meta-analytic Diversity. *Academy of Management Journal* , 52, 599-627.
66. Joy, S., & Kolb, D. A. (2009). Are There Cultural Differences in Learning Style? *International Journal of Intercultural Relations* , 33, No. 1, 69-85.
67. Jung, C. (1921). *Psychological Types.* Zurich: Rascher Verlag.
68. Katzenbach, J., & Smith, D. (1993). *The Wisdom of Teams: Creating the High-Performance Organization.* Boston: Harvard Business School Press.
69. Kayes, A. B., Hayes, D. C., & Kolb, D. A. (2005). Experiential Learning in Teams. *Simulation & Gaming* , 36, No. 3, 330-354.
70. Kayes, D. C. (2005). Internal Validity and Reliability of Kolb's Learning Style Inventory Version 3. *Journal of Business and Psychology* , 20, No. 2, 249-257.
71. Kearney, E., Gebert, D., & Voelpel, S. C. (2009). When and How Diversity Benefits Teams: The Importance of the Team Members' Need for Cognition. *Academy of Management* , 52, 581-596.
72. Keller, R. T. (2001). Cross-functional Project Groups in Research and New Product Development: Diversity, Communications, Job Stress, and Outcomes. *Academy of Management Journal* , 44, No. 3, 547-555.
73. Kolb, A. Y., & Kolb, D. A. (2005). *The Kolb Learning Style Inventory - Version 3.1.* Boston, MA: Hay Group.
74. Kolb, A. Y., & Kolb, D. A. (2005). *The Kolb Learning Style Inventory— Version 3.1, 2005 Technical Specifications.* Hay Group.
75. Kolb, D. A. (1973). *Management and the Learning Process.* Cambridge, MA: MIT Alfred P. Sloan School of Management.
76. Kolb, D. A. (1981). Experiential Learning Theory and the Learning Style Inventory: A Reply to Freedman and Stumpf. *The Academy of Management Review* , 6, No. 2, 289-296.
77. Kolb, D. A. (1984). *Experiential Learning: Experience as the Source of Learning and Development.* Englewood Cliffs, New Jersey: Prentice Hall.
78. Kolb, D. A., Boyatzis, R. E., & Mainemelis, C. (2001). Experiential Learning Theory: Previous Research and New Directions. *Perspectives on Thinking, Learning, and Cognitive Styles 1* , 227-247.
79. Kozlowski, S. W., Gully, S. M., Nason, E. R., & Smith, E. M. (1999). The Changing Nature of Performance: Implications for Staffing, Motivation, and Development. In D. R. Ilgen, & E. D. Pulakos, *Developing*

Adaptive Teams: A Theory of Compilation and Performance Across Levels and Time (pp. 240-292). San Francisco, CA: Jossey Bass Publishers.
80. Kvadias, S., & Sommer, S. C. (2009). The Effects of Problem Structure and Team Diversity on Brainstorming Effectiveness. *Management Science* , 55, No. 12, 1899-1913.
81. Lai, J., Honda, T., & Yang, M. C. (2010). A Study of the Role of User-Centered Design Methods in Design Team Projects. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing* , 24, No. 3, 303-316.
82. Lawrence, B. S. (1997). The Black Box of Organizational Demography. *Organization Science* , 8(1), 1-22.
83. Lear, T. F. (1957). *Interpersonal Diagnosis of Personality.* New York: Ronald Press.
84. Leary, T. (1957). *Interpersonal Diagnosis of Personality.* NY: Ronald Press Co.
85. Leonard, N. H., Scholl, R. W., & Kowalski, K. B. (Journal of Organizational Behavior). *Information Processing Style and Decision Making.* 1999: 20, No. 3, 407-420.
86. Lesmes-Anel, J., Robinson, G., & Moody, S. (2001). Learning Preferences and Learning Styles: A Study of Wessex General Practice Registrars. *The British Journal of General Practice* , 51, No. 468, 559.
87. Liang, J. S. (2012). The Effects of Learning Styles and Perceptions on Application of Interactive Learning Guides for Web-Based Courses. *AAEE* (pp. 1-10). Melbourne, Australia: Yung-Ta Institute of Technology and Commerce.
88. Lin, Z., Yang, H., Arya, B., Huang, Z., & Li, D. (2005). Structural Versus Individual Perspectives on the Dynamics of Group Performance: Theoretical Exploration and Empirical Investigation. *Journal of Management , 31* (3), 354-380.
89. Loo, R. (2002). A Meta-Analytic Examination of Kolb's Learning Style Preferences Among Business Majors. *Journal of Education for Business* , 77, No. 5, 252-56.
90. Loo, R. (2002). A Meta-Analytic Examination of Kolb’s Learning Style Preferences Among Business Majors. *Journal of Education for Business , 77* (5), 252-256.
91. Loo, R. (2004). Kolb's Learning Styles and Learning Preferences: Is There a Linkage? *Educational Psychology* , 24, No. 1, 99-108.
92. Lovelace, K., Shapiro, D. L., & Weingart, L. R. (2001). Maximizing Cross-Functional New Product Teams' Innovativeness and Constraint Adherence: A Conflict Communications Perspectives. *The Academy of Management Journal* , 44, No. 4, 779-793.
93. Lu, H., Jia, L., Gong, S.-h., & Clark, B. (2007). The Relationship of Kolb Learning Styles, Online Learning Behaviors and Learning Outcomes. *Educational Technology & Society , 10* (4), 187-196.
94. Lumsdaine, M., & Lumsdaine, E. (1995). Thinking Preferences of Engineering Students: Implications for Curriculum Restructuring. *Journal of Engineering Education* , 84, No. 2, 193-204.
95. Madhavan, R., & Grover, R. (1998). From Embeddeed Knowledge to Embodied Knowledge: New Product Development as Knowledge Management. *Journal of Marketing* , 62, No. 4, 1-12.
96. Mammen, J., Fischer, D. R., Anderson, A., James, L. E., Nussbaum, M. S., Bower, R. H., et al. (2007). Learning Styles Vary Among General Surgery Residents: Analysis of 12 Years of Data. *Journal of Surgical Education* , 64, No. 6, 386-389.
97. Manolis, C., Burns, D. J., Assudani, R., & Chinta, R. (2013). Assessing Experiential Learning Styles: A Methodological Reconstruction and Validation of the Kolb Learning Style Inventory. *Learning and Individual Differences* , 23, 44-52.
98. Marton, F., & Saljo, R. (1976). Qualitative Differences in Learning: Outcome and Process. *British Journal of Educational Psychology* , 46, 4-11.
99. McGrath, R. G., MacMillan, I. C., & Venkataraman, S. (1995). Defining and Develo;ping Competence: A Strategic Process Paradigm. *Strategic Management Journal , 16* (4), 251-275.
100. McKenna, A. F., & Hirsch, P. (2005). Evaluating Student Confidence in Engineering Design, Teamwork, and Communication. *ASEE*, (pp. 1-11). Evanston, IL.
101. Milliken, F. J., & Martins, L. L. (1996). Searching for Common Threads: Understanding the Multiple Effects of Diversity in Organizations Work Groups. *Academy of Management Review* , 21, 402-433.
102. Mohammed, S. (2001). Toward an Understanding of Cognitive Consensus in a Group Decision-Making Context. *Journal of Applied Behavioral Science , 37* (4), 408-425.
103. Montgomery, S. M., & Groat, L. N. (1998). Student Learning Styles and Their Implications for Teaching. *CRLT Occasional Papers* , 10, 1-8.
104. Myers, I. B., & McCaulley, M. H. (1985). *Manual: A Guide to the Development and Use of the Myers-*

Briggs Type Indicator. Palo Alto: Consulting Psychologists Press.

105. Neuhauser, C. (2002). Learning Style and Effectiveness of Online and Face-to-face Instruction. *The American Journal of Distance Education* , 16, No. 2, 99-113.

106. Neuman, G. A., Wagner, S. H., & Christiansen, N. D. (1999). The Relationship Between Work-team Personality Composition and the Job Performance of Teams. *Group & Organization Management* , 24, No. 1, 28-45.

107. Newland, P., Powell, J. A., & Creed, C. (1987). Understanding architectural designers' selective information handling. *Design Studies , 8* (1), 2-16.

108. Newland, P., Powell, J. A., & Creed, C. (1987). Understanding Architectural Designers' Selective Information Handling. *Design Studies* , 8, No. 1, 2-16.

109. Oberoi, S., Finger, S., & Rose, E. (2013). Online Implementation of the Delta Design Game for Analyzing Cllaborative Team Practices. *ASME IDETC and CIE*, (pp. 1-7). Portland, OR.

110. Owen, C. (2007). Design Thinking: Notes on its Nature and Use. *Design Research Quarterly* , 2, No. 1, 16-27.

111. Pask, G. (1988). Learning Strategies, Teaching Strategies, and Conceptual or Learning Style. In *Learning Stragegies, Learning Styles* (pp. 83-100). New York: Springer US.

112. Peelle III, H. E. (2006). Appreciative Inquiry and Creative Problem Solving in Cross-Functional Teams. *The Journal of Applied Behavioral Science, , 42* (4), 447-467.

113. Peeters, M. A., Van Tuijl, H. F., Rutte, C. G., & Reymen, I. M. (2006). Personality and Team Performance: A Meta-Analysis. *European Journal of Personality* , 20, No. 5, 377-396.

114. Philbin, M., & Meier, E. (1995). A Survey of Gender and Learning Styles. *Sex Roles* , 32, No. 7, 485-494.

115. Pine, J. B., & Gilmore, J. H. (1999). *The Experience Economy.* Boston: Harvard Business School Press, Boston.

116. Poling, T., Woehr, D. J., Arciniega, L. M., & Gorman, A. (2004). The Impact of Personality and Value Diversity on Team Performance. *Annual Conference of the Society for Industrial and Organizational Psychology.* Tallin, Estonia.

117. Randel, A. E., & Jaussi, K. S. (2003). Functional Background Identity, Diversity, and Individual Performance in Cross-Functional Teams. *The Academy of Management Journal* , 46, No. 6, 763-774.

118. Rasmussen, K. L. (1998). Hypermedia and Learning Styles: Can Performance be Influenced? *Journal of Multimedia and Hypermedia* , 7, No. 4, 291-308.

119. Rayner, S., & Riding, R. (1997). Towards a Categorisation ofCognitive Styles and Learning Styles. *Educational Psychology* , 17, No. 1-2, 5-27.

120. Recchia, T., Chung, J., & Pochiraju, K. (2013). Improving Learning in Robot Teams Through Personality Assignment. *Biologically Inspired Cognitive Architectures* , 3, 51-63.

121. Rhee, J., Parent, D., & Basu, A. (2013). The Influence of Personality and Ability on Undergraduate Teamwork and Team Performance. *Springer Plus* , 2-16.

122. Romanelli, F., Bird, E., & Ryan, M. (2009). Learning Styles: A Review of Theory, Application, and Best Practices. *American Journal of Pharmaceutical Education* , 73, No. 1, 1-5.

123. Rosati, P., & Rosati, P. (1999). Specific Differences and Similarities in the Learning Preferences of Engineering Students. *ASEE/IEEE FIE.* San Juan, Puerto Rico.

124. Rothwell, J. D. (2004). *In Mixed Company: Communicating in Small Groups and Teams.*

125. Saracho, O. N. (1993). The Effects of the Teachers' Cognitive Styles on Their Students' Academic Achievement. *International Journal of Early Childhood* , 25, No. 2, 37-40.

126. Schaller, Borun, Allison-Bunnell, & Chanbers, (2007), One Size Does Not Fit All: Learning Style, Play and On-line Activities. *Museums and the Web 2007: Proceedings*. Toronto

127. Schippers, M. C., Den Hartog, D. N., Koopman, P. L., & Wienk, J. A. (2003). Diversity and Team Outcomes: The Moderating Effects of Outcome Interdependence and Group Longevity and the Mediating Effect of Reflexivity. *Journal of Organizational Behavior* , 24, No. 6, 779-802.

128. Schmidt, J. B., Montoya-Weiss, M. M., & Massey, A. P. (2001). New Product Development Decision-Making Effectiveness: Comparing Individuals, Face-To-Face Teams, and Virtual Teams. *Decision Sciences* , 32, No. 4, 575-600.

129. Sethi, R. (2000). New Product Quality and Product Development Teams. *The Journal of Marketing* , 1-14.

130. Sethi, R. (2000). Superordinate Identity in Cross-Functional Product Development Teams: Its Antecedents and Effect on New Product Performance. *Journal of the Academy of Marketing Sicence* , 28, No. 3, 330-344.

131. Sethi, R., Smith, D. C., & Park, C. W. (2001). Cross-Functional Product Development Teams, Creativity, and the Innovativeness of New Consumer Products. *Journal of Marketing Research* , 38, No. 1, 73-85.
132. Severiens, S. E., & Dam, G. T. (1994). Gender Differences in Learning Styles: A Narrative Review and Quantitative Meta-Analysis. *Higher Education* , 27, No. 4, 487-501.
133. Severiens, S., & Dam, G. T. (1997). Gender and Gender Identity Differences in Learning Styles. *Educational Psychology* , 17, No. 1-2, 79-93.
134. Shikhar, S., & McDermott, C. (n.d.). The Effect of Team Leader Characteristics on Learning, Knowledge Application, and Performance of Cross-Functional New Product Development Teams. *Decision Sciences* , 34, No. 4, 707-739.
135. Shoobridge, G. E. (2006). Multi-Ethnic Workforce and Business Performance: Review and Synthesis of the Empirical Literature. *Human Resource Develoment Review , 5* (1), 92-137.
136. Sole, D., & Applegate, L. (2000). Knowledge Sharing Practices and Technology Use Norms in Dispersed Development Teams. *Twenty First International Conference on Information Systems* (pp. 581-587). Atlanta, GA: Association for Information Systems.
137. Song, X. M., Neeley, S. M., & Zhao, Y. (1996). Managing R&D - Marketing Integration in the New Product Development Process. *Industrial Marketing Management* , 25, No. 6, 545-553.
138. Swink, M. (2000). Technological Innovativeness as a Moderator of New Product Design Integration and Top Management Support. *Journal of Product Innovation Management* , 17, No. 3, 208-220.
139. Tezel, E., & Casakin, H. (2010). Learning Styles and Students' Performace in Design Problem Solving. *International Journal of Architectural Research* , 4, No. 2-3.
140. Troy, L. C., Hirunyawipada, T., & Paswan, A. K. (2008). Cross-Functional Integration and New Product Success: An Empirical Investigation of the Findings. *Journal of Marketing* , 72, No. 6, 132-146.
141. Tuckman, J., & Lorge, I. (1962). Individual Ability as a Determinant of Group Superiority. *Human Relations* , 15, 45-51.
142. Tumlinson, J. (2012 йил 5-July). *Adverse Selection in Team Formation Under Discrimination*. From Social Science Research Network: http://sswn.com/abstract=2101064
143. Tyran, K. L., & Gibson, C. B. (2008). Is What YOu See, What You Get?: The Relationship Aong Surface- and Deep-Level Heteorgeneity Characteristics, Group Efficacy, and Team Reputation . *Group & Organization Management , 33* (1), 46-76.
144. Valenti, M. A., & Rockett, T. (2008). The Effects of Demographic Differences on Forming Intragroup Relationships. *Small Group Research , 39*, 179-202.
145. Van Der Vegt, G. S., & Janssen, O. (2003). Joint Impact of Interdependence and Group Diversity on Innovation. *Journal of Management* , 29, No. 5, 729-751.
146. Van der Vegt, G. S., & Van de Vliert, E. (2005). Effects of Perceived Skill Dissimilarity and Task Interdependence on Helping in Work Teams. *Journal of Management , 31* (1), 73-89.
147. Van Knippenberg, D. A., De Dreu, C. K., & Homan, A. C. (2004). Work Group Diversity and Group Performance: An Integrative Model and Research Agenda. *Journal of Applied Psychology* , 89, 1008-1022.
148. Van Zwanenberg, N., Wilkinson, L. J., & Anderson, A. (2000). Felder and Silverman's Index of Learning Styles and Honey and Mumford's Learning Syles Questionnaire: How Do They Compare and Do They Predict Academic Performance? *Educational Psycholoogy* , 20, No. 3, 365-380.
149. Watson, G. B. (1928). Do Groups Think More Effectively Than Individuals? *Journal of Abnormal and Social Psychology* , 23, 328-336.
150. Williams, K., & O'Reilly, C. (1998). The Complexity of Diversity: A Review of Forty Years of Research. *Research in Organizational Behavior* , 21, 77-140.
151. Wilson, E. (1994). Improving Market Success Rates through Better Product Definition. *World Class Design to Manufacture , 07*, 13-15.
152. Woolley, A. W., Chabris, C. F., Pentland, A., Hashmi, N., & Malone, T. W. (2010). Evidence for a Collective Intelligence Factor in the Performance of Human Groups. *Science* , 330, No. 6004, 686-688.
153. Zirger, B. J., & Maidique, M. A. (1990). A Model of New Product Development: An Empirical Test. *Management Science , 36* (7), 867-883.