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Diversity in Design Teams: An Investigation of Learning Styles and their Impact on Team Performance and Innovation*

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In this paper, we examine the role of diversity in design team performance, and discuss how diversity factors affect the dynamics and success of a design team. In particular, we focus on diversity in learning styles, as defined by Kolb's Experiential Learning Theory. We also consider other demographic factors, such as discipline and gender. We present data gathered over two semesters of a multidisciplinary, project-based graduate level design course offered at the University of California at Berkeley. The data were captured through a series of surveys administered during the semester, first to collect diversity information on learning styles and standard demographics, and then to assess team performance as students reflected on their team interactions. We examine and compare the overall learning style breakdown of students in the class, along with an analysis of the teams. The results of our analyses offer insights into how students with different learning styles appear to contribute to design team performance. We provide recommendations that will help inform design educators on how to enhance overall team performance and innovation, with an understanding of learning style differences.

Keywords: learning styles; design teams; team performance; Kolb's experiential learning

1. Introduction and background

With ever-changing technologies and rising market competition, it is increasingly important to design innovative products. Teamwork leads to innovation more frequently than individual efforts [1], and organizations that focus on new product development invest in developing their teams to achieve a high level of creativity and innovation. This begs the question of how to best form and manage teams that will successfully build quality products. For example, should teams consist of experts from the same field and with similar reinforcing experiences, or should the teams be composed of experts from diverse backgrounds and personality types? Many companies rely on cross-functional teams to benefit from diverse perspectives, experiences, and design-for-X expertise, including members from engineering, business, industrial design, and more [2].

A variety of diversity factors may affect new product development team performance outcomes. Individual differences—be they cultural, gender, or cognitive—cause people to approach a single situation in various ways. In the academic setting, such differences may influence how a person learns, solves problems, and interacts with peers and team members.

In recent years, design education researchers have begun exploring the relationship between learning styles and learning in design. From this research, a variety of learning characterizations have been identified. Newland categorizes learners as common sense, dynamic, contemplative, and zealous [3]. Leary classifies a person's behavior along two axes: dominant versus submissive and friendly versus critical [4]. Felder examines learning under sensory versus intuitive, visual versus auditory, inductive versus deductive, and active versus reflective dimensions [5].

In his Experiential Learning Theory (ELT), Kolb posits that a person acquires knowledge by grasping and transforming experience [6, 7]. He defines these experiences along two dialectically related continua: Concrete Experience (CE) or Abstract Conceptualization (AC), which measure how an individual perceives information, and Reflective Observation (RO) or Active Experimentation (AE), which measure how an individual processes information. These two continua intersect to create four quadrants, each representing a different learning style (Fig. 1). Each individual's learning style is deter-

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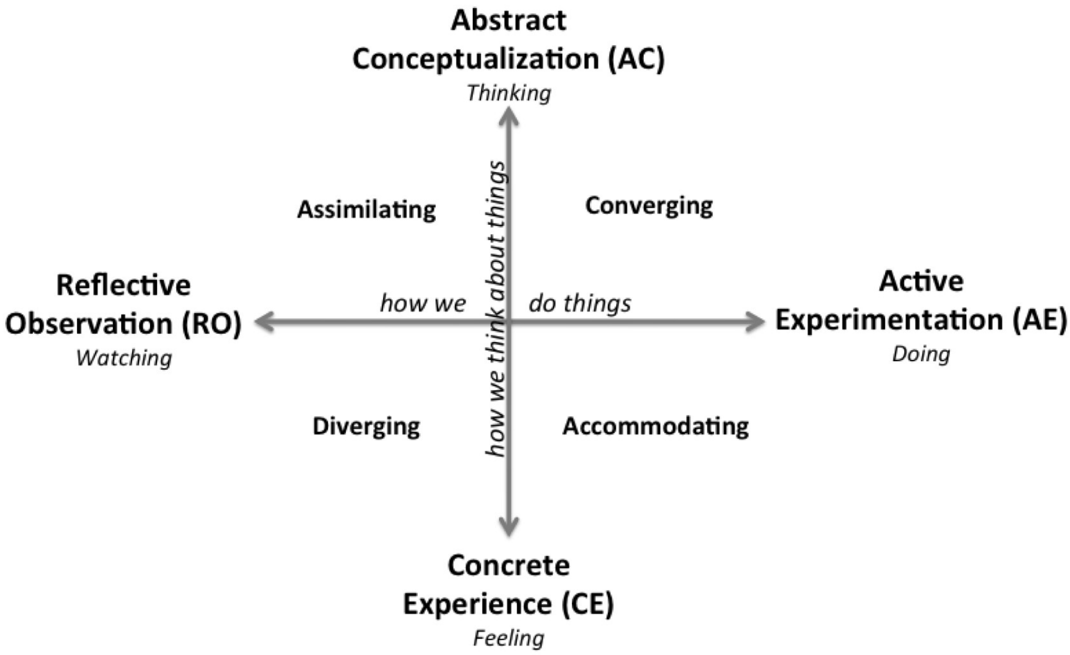

Fig. 1. Kolb Learning Styles. [6]

mined by which combination of learning modes he or she prefers for perceiving and processing information.

The five learning styles are:

1. Assimilating (Abstract Conceptualization and Reflective Observation): best at synthesizing a wide range of information into a useful, logical form
2. Converging (Abstract Conceptualization and Active Experimentation): logical and organized, good at finding practical applications for ideas and theories
3. Accommodating (Concrete Experience and Active Experimentation): hands-on learning, practical experience, sensing and intuitive risk-takers
4. Diverging (Concrete Experience and Reflective Observation): best at viewing concrete situations from many different points of view, facilitate idea generation
5. Balanced (Abstract Conceptualization and Concrete Experience or Reflective Observation and Active Experimentation): has no strong preference for either extreme of the Processing or Perception continuums combined, well-balanced

Learning styles are particularly relevant to design for its connection to innovation as a learning process [8]. Although there have been extensive studies relating to learning styles, research surrounding Kolb learning styles in design teams has not yet been fully explored. In this paper, we will examine the effect of learning styles on design team performance in the educational setting.

2. Subjects and methods

For this study, we gathered data 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 [9].

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 1 shows the breakdown of students, by discipline and gender.

We conducted this study 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

Table 1. Class breakdown by discipline and gender—Fall 2009 and 2010, combined

	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

personal styles in observations, framing, and thinking, 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, we administered a Peer Review and Team Assessment survey 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, in such ways as 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 different in each year.

3. Results and discussion

3.1 Learning styles of study population versus general population

The distribution of learning styles in our entire study population is shown in Fig. 2. Overall, the class has a relatively similar learning style breakdown between the Fall 2009 and 2010 groups. The students with a converging learning style are most dominant across both semesters. The only difference is the marked paucity 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 our 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 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 [7, p. 13].

Learning styles are also connected to our educational and professional experiences as shown by a number of studies examining learning styles and educational or career interests [10–13]. Kolb posits that some learning styles will be typical in certain vocations, because of the experiences one undertakes in studying a specific profession [6, 11]. For

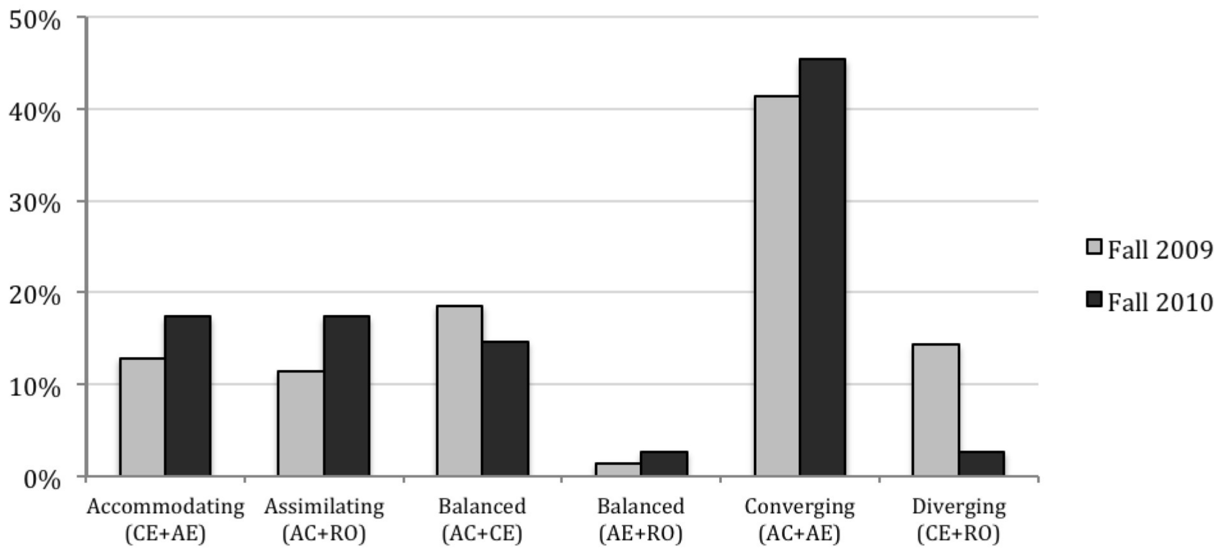

Fig. 2. Learning Styles of Design Students.

Table 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 3. Learning Styles by discipline—Fall 2009 and 2010, combined

	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**

'Other' represents the Science and Humanities fields, such as Genetics and Plant Biology, Art History, and Information Science.

instance, Kolb found that individuals in human-related professions (educators, social workers, nursing) tended towards concrete learning and were more likely to be accommodators [7]. Engineers and decision-makers were high in converging learning styles, whereas professionals in the arts and humanities were high in diverging styles. Mathematicians and scientists mostly preferred the assimilating learning style.

In our study group, the converging learning style is most dominant (Table 3). This is not surprising given the number of engineers and business students in the class. However, there is a significant paucity of divergers, except among the Industrial Design students.

When comparing learning styles by gender, women and men typically demonstrate different learning style preferences [6]. 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 [14,15] with either Diverging or Accommodating learning styles.

In our study population, a higher percentage of women exhibit the Assimilating learning style over the Diverging learning style, and also have a higher percentage of Assimilators than men (Table 4). On the other hand, Kolb also found that learning styles either changed over one's academic career, or else universities and graduate schools favor students with higher Abstract Conceptualization (assimilating or converging). So it is not surprising that AC was high for both men and women in our graduate course, with the male percentage higher.

Table 4. Learning styles by gender—Fall 2009 and 2010, combined

	Female	Male
Accommodating	8 (19%)	14 (14%)
Assimilating	7 (17%)	14 (13%)
Balanced	9 (21%)	18 (17%)
Converging	14 (33%)	49 (47%)
Diverging	4 (10%)	8 (8%)
Total	42	103

3.2 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). In Fig. 3, we illustrate 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.

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 a much longer line in the 'Diverging' quadrant, representing its more dominant learning style, while Team 2's line is longest between AC and AE in the 'Converging' region. The Class Average falls between these two profiles and shows a stronger preference for converging.

3.3 Learning styles and team assessment results

With these aggregated learning style profiles, we then examine how design teams rated themselves on the mid-semester surveys to understand team coher-

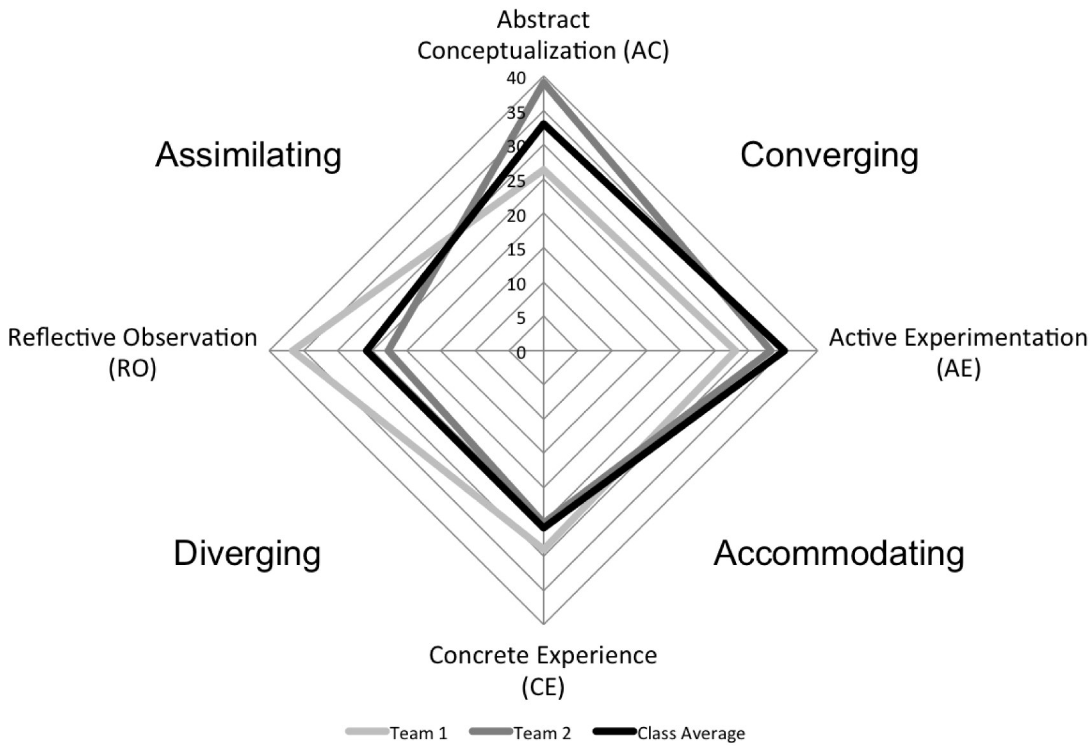

Fig. 3. Learning Style Profiles.

ence and performance. We compare design teams with respect to the number of convergers within the team because of the converging dominance in the class. Tables 5 and 6 show the results of the mid-semester survey, evaluated against the number of convergers on a team for Fall 2009 and Fall 2010 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 reflective dialogue within the team, and limited or slower success in teamwork.

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

Table 5. 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. 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***

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.

3.4 *Learning styles and team performance results*

Table 7 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.

We observe 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 8 shows the team's actual project score by

Table 7. 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 8. 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

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.

We note in Table 8 that of the eleven teams with only one converger, six appear in the top ten of the list of highest performing teams. We also note that 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 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.

We also compared the grades 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 we compare the teams by the number of convergers with their final team grades, we reveal some interesting relationships. In Fig. 4, we see a high, statistically significant correlation between how productive teams with one converger believe their meetings to be and their final project grade.

3.5 Learning styles and combined mid- and end-of-semester analysis

Table 9 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

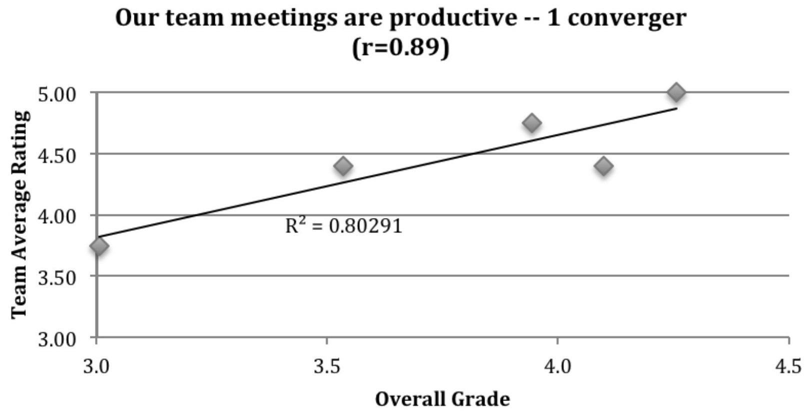

Fig. 4. Mid-semester Evaluations versus Overall Project Score.

Table 9. Midterm 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***

ones in bold being statistically significant. Here, we see the Converging and Balanced students showing 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.

4. Conclusions and recommendations

In this paper, we explored the Kolb learning styles of students in a graduate-level design course over two semesters. We found that the students in this course were most dominant in the converging learning style, and most lacking in the diverging learning style. We 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, we cannot draw any other conclusions on the benefits of diversity in learning styles. We do plan future research on small projects composed of teams with homogeneous learning styles to investigate learning style diversity impacts on teamwork further.

We note 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.

We 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.

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