Global Characterizations of Learning Styles among Students and Professionals

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Abstract

In this paper, we compare the learning styles of college students and professionals in design, engineering and business at various universities and organizations around the world. We focus on learning styles as defined by David Kolb's Experiential Learning Theory, and also consider factors such as gender, ethnicity, and discipline. We collected data from undergraduate-level and graduate-level students and also present data gathered from industry professionals in various design, engineering, and consulting firms in the United States and Australia. In our analyses, we draw comparisons among the international populations, as well as across fields of expertise and other demographics. The results allow us to characterize the learning styles of "engineers and managers" and discuss the implications for their education.

I. Introduction and Background

Reports from the National Academies and accreditation agencies stress the importance of preparing engineers to be successful in a global, multidisciplinary workforce [1,2,5,17,18,19,21]. In this paper, we attempt to understand the dimensions of such a workforce by capturing and comparing learning styles in various populations across the world. In particular, we study learning styles as defined by David Kolb's Experiential Learning Theory [13,14]. Although there are many excellent tools available for assessment of learning or cognitive styles (e.g. Herrmann Brain Dominance Instrument [11,16], Index of Learning Styles [9,10], Big Five Personality Test [6,7]), we used the validated Kolb instrument because of its accessibility for research, shorter length questionnaire, the ability to benchmark against prior work [15], and its match with models of design or design thinking that we are teaching [3,4].

The Kolb model is based on the idea that "knowledge is created through the transformation of experience" and is defined by two main axes: *how we think about things* (Perception) and *how we do things* (Processing) [13,14]. These axes compose four quadrants, which represent the different learning styles: accommodating, assimilating, converging, and diverging (Figure 1). People may also have their strengths best represented on the extreme ends of the perception or processing axis, rather than in one of the quadrants. In these cases, the learning style is defined as "balanced-processing" (balanced between reflective observation and active experimentation) or "balanced-perception" (balanced between abstract conceptualization and concrete experience). According to early reports by Kolb, young children show an even balance of all learning styles, but move towards more abstract thinking as they grow older [14]. A recent study found that one-third of adults were converging, another third were assimilating, 20% were accommodating, and less than 10% were divergent [25].

Beckman and Barry [4] have found Kolb learning styles useful in considering the capabilities that designers and engineers need to move fluidly between concrete and abstract worlds, and to use both analysis and synthesis to create new designs. For instance, design teams may begin with observations (thus diverging), then build frameworks (through assimilating), settle on a list of imperatives (converging), and finally construct artifacts of their design solutions (accommodating) (Figure 2). It is important to note that the best results are obtained when the students iterate through this cycle (i.e. the four quadrants) multiple times. As such, successful design teams must collectively demonstrate all four learning styles in the design process.

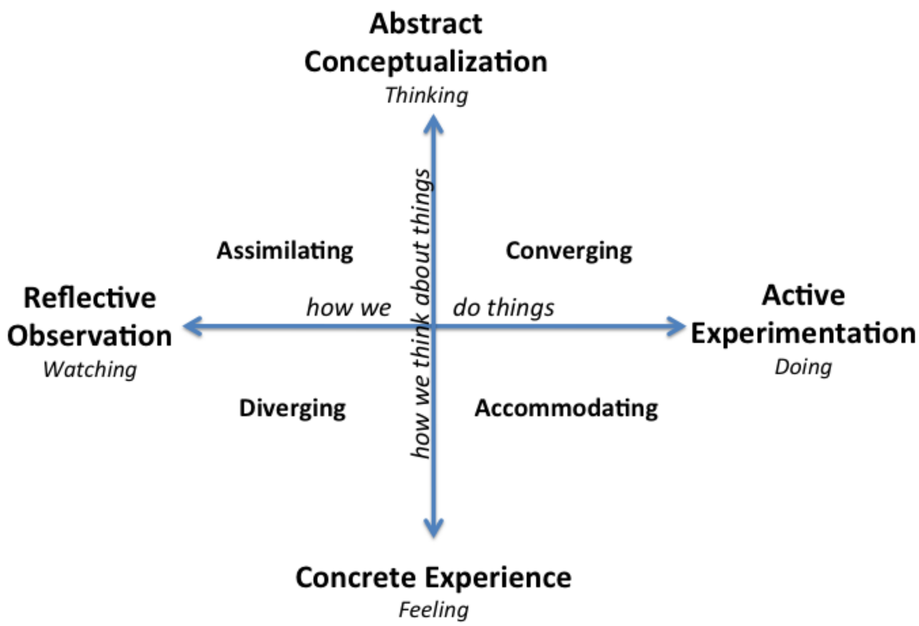

Figure 1: Kolb Learning Styles

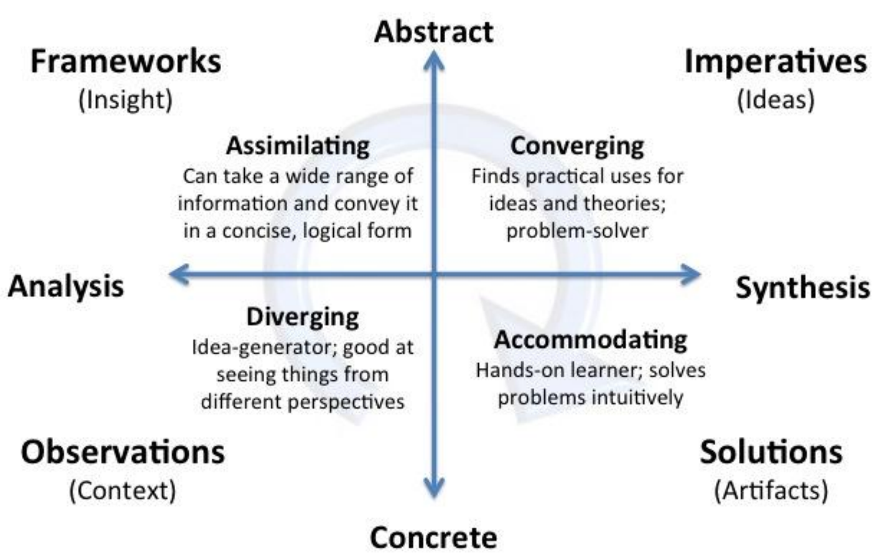

Figure 2: Learning Styles and the Design Process [4]

In this paper, we attempt to understand the various populations that engage in design activities – designers, engineers and businesspeople – by performing international and disciplinary comparisons of learning styles and comparing learning styles against demographic data, in particular – gender.

II. Survey Populations and Methods

Our data were gathered from a number of different populations, including both students and professionals (Table 1). Among the students, we have undergraduate and graduate populations from engineering, business administration, and other disciplines within the sciences and humanities.

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 [24].
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.

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

From industry we collected data on a mix of professionals primarily from engineering and business, 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). We also captured data from several executive education programs held by UC Berkeley at which a variety of industries were represented.

Table 1: Overall Survey Population

	Number of Participants
Industry	1199
Undergraduate	881
Graduate	1431
Total	**3511**

The data were collected via online surveys administered to the groups at the beginning of their classes (for the students) or programs (for the professionals). We collected information about learning styles, as well as demographic data about gender, ethnicity, job title (where applicable), and undergraduate major.

III. Results and Discussion

A. Comparison of Learning Styles By Gender

We start by seeking to determine whether or not the four learning styles are equally represented across genders. Table 2 shows the distribution of learning styles by gender. We use Pearson's Chi-Squared Test for categorical data to find 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 populations.

Table 2: Distribution of Learning Styles in the Entire Study Population

	Entire Study Population			
	Female		Male	
Accommodating	186	16%	233	10%
Assimilating	225	19%	607	25%
Balanced - Perception	77	7%	166	7%
Balanced - Processing	187	16%	245	10%
Converging	429	37%	1114	46%
Diverging	63	5%	81	3%
Grand Total	**1167**		**2446**	

Table 3 summarizes the p-values for the significance of gender differences in each of the target populations in our study. We find statistical significance ($p \leq 0.05$) in six instances (highlighted in Table 3), suggesting that learning styles are different by gender in certain circumstances. Overall, we find a statistically significant difference in learning styles between females and males at aggregate levels, such as in the entire population of subjects.

Table 3: Statistical Significance of Gender Differences in Each of the Study Populations

	Gender	**p-value**
1	Entire population	**0.00**
2	Industry	0.09
3	Graduates (All)	**0.00**
4	Graduates (Engineering)	0.29
5	Graduates (MBA)	**0.00**
6	Undergraduates (All)	**0.01**
7	Undergraduates (KAIST)	0.49
8	Undergraduates (Business Administration)	**0.02**
9	Undergraduates (Engineering)	0.13
10	Undergraduates (IDP)	**0.03**

When we break down the overall population, we find that not all groups show statistically significant differences by gender. Collectively, the population of all graduate students ($p = 0.00$), the population of all MBA students ($p = 0.00$), the population of all undergraduate students ($p = 0.01$), and all undergraduate business students ($p = 0.02$) show significant differences by gender. The industry population on its own ($p = 0.09$), graduate engineering students ($p = 0.29$), undergraduate engineering students ($p = 0.13$), and KAIST students ($p = 0.49$) do not show any statistically significant gender-related learning style differences. Perhaps the most interesting result here is that engineering students do not show gender differences while MBA and other student populations do.

A comparison of the distributions of learning styles among graduate MBA and engineering students is presented in Table 4, which highlights where some of the differences lie. In particular, it is interesting to observe that there are zero students with diverging learning styles among the engineering population at the graduate level.

A similar pattern emerges in an analysis of the undergraduate student population (Table 5). Just as for the graduate students, the learning styles of the undergraduate student population as a whole differ by gender (p = 0.02).

Table 4: Distribution of Learning Styles in Graduate Business and Engineering Students

	MBA				**Engineering**			
	Female		Male		Female		Male	
Accommodating	59	16%	62	7%	5	15%	5	6%
Assimilating	62	17%	218	25%	8	24%	15	19%
Balanced - Perception	10	3%	36	4%	0	0%	4	5%
Balanced - Processing	54	15%	75	9%	7	21%	9	11%
Converging	155	43%	469	53%	13	39%	47	59%
Diverging	23	6%	18	2%	0	0%	0	0%
Grand Total	**363**		**878**		**33**		**80**	

Table 5: Distribution of Learning Styles in Undergraduate Students

	Undergraduates			
	Female		Male	
Accommodating	59	17%	66	13%
Assimilating	59	17%	117	23%
Balanced - Perception	38	11%	46	9%
Balanced - Processing	76	22%	77	15%
Converging	97	28%	177	34%
Diverging	20	6%	35	7%
Grand Total	**349**		**518**	

However, when we examine the individual populations of undergraduate students, by discipline or country (Table 6), we see that the more technical populations (KAIST and UCB Engineering) do not show statistically significant gender differences. By contrast, the learning styles of the less technical 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. This reveals an intriguing pattern, in which engineers or those in more technical fields seem to have no significant gender differences in Kolb learning styles. The gender neutral results in the technical student population could be due to a bias in self-selection or in socialization in technical majors.

Table 6: 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%	12%	8%	15%	8%	15%	14%
Assimilating	13%	20%	18%	32%	19%	16%	18%	27%
Balanced - Perception	15%	4%	3%	11%	12%	2%	11%	13%
Balanced - Processing	34%	34%	21%	0%	8%	21%	15%	12%
Converging	11%	27%	41%	49%	27%	34%	34%	28%
Diverging	2%	0%	6%	0%	19%	19%	7%	5%
Grand Total	**123**	**56**	**34**	**37**	**26**	**106**	**131**	**269**

B. Comparison of Learning Styles by Status, Discipline and Geographic Location

There are several other factors besides gender that distinguish the populations we studied, including status, discipline, and geographical location. In this section, we describe the outcome of comparisons of learning styles across these dimensions. The results of comparisons across academic institutions for the undergraduate students are summarized in Table 7, with statistical significance signified by p-value < 0.05. In this table, "US Universities" is an aggregate of data from UCB, CCA and IDP.

Table 7: Statistical Significance of Learning Style Differences between Undergraduate Populations by Institution and Major

	Undergraduate Students	p-value
1	KAIST vs. US Universities	**<u>0.00</u>**
2	KAIST vs. IDP	**<u>0.00</u>**
3	KAIST vs. UCB (Engineering)	**<u>0.00</u>**
4	KAIST vs.UCB (Business Admin)	**<u>0.02</u>**
5	KAIST vs. CCA	0.72
6	CCA vs. UCB (Engineering)	0.49
7	CCA vs. IDP	0.22
8	IDP vs. UCB (Engineering)	**<u>0.00</u>**

The results for the Korean university students are most striking (Rows 1-5 in Table 7), as they show significantly 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 our study population. Both KAIST and UCB (Engineering) show up as different than the population at IDP, suggesting that there is a difference in learning styles between engineering-focused students and design-focused ones.

Alternatively, we see high statistical difference between the IDP students with the UCB Engineering students ($p = 0.00$), which is expected. Table 8 shows the learning styles of the undergraduate populations.

Table 8: Learning Style Distribution of Undergraduate Population by Institution

	KAIST		UCB (Engr)		UCB (BA)		IDP		CCA	
Accommodating	58	15%	15	10%	8	8%	39	22%	5	17%
Assimilating	97	24%	22	15%	26	27%	27	15%	5	17%
Balanced - Perception	49	12%	5	3%	6	6%	20	11%	2	7%
Balanced - Processing	53	13%	27	18%	10	10%	61	34%	6	21%
Converging	120	30%	44	29%	45	46%	29	16%	10	34%
Diverging	23	6%	37	25%	3	3%	3	2%	1	3%
Grand Total	**400**	**100%**	**150**	**100%**	**98**	**100%**	**179**	**100%**	**29**	**100%**

Table 9: Learning Style Distribution of Professional Population compared with Student Population

	Industry Professionals		Student Population	
Accomodating	146	12%	256	12%
Assimilating	301	25%	479	22%
Balanced - Perception	101	8%	134	6%
Balanced - Processing	94	8%	298	13%
Converging	515	43%	958	43%
Diverging	41	3%	96	4%
Grand Total	**1198**	**100%**	**2221**	**100%**

We also compared the entire student population with the professional population (Table 9). At the aggregate level, the populations show no statistically significant difference in learning styles.

However, the fact that the aggregate student population shows learning style differences between genders (p<0.05) while the industry population does not (p = 0.09) is interesting. This could be the result either of selection on the part of these organizations or of the effects of working in these organizations on the population. As Kolb suggests [25], learning styles can change over time and adapt to the environment in which the person is working. It is possible that the gender-based learning style differences are disappearing as the students adapt themselves to the learning approaches required in these organizations.

Comparison of Learning Styles by Ethnicity

We also explored learning styles and ethnicities, but did not find statistical significance (p<0.05) in any of the populations from which we collected ethnicity information (Table 10). This is an intriguing result, as we did find 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.

Table 10: 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

Discussion

Previous research has shown that women and men have different learning styles [25, 26], with females more strongly represented in the divergent and accommodating styles than males [27]. Our study provides more nuanced insight into this general research. Although we indeed found that men and women in business school have statistically significant different styles, with more women who are accommodating and diverging learners, these differences did not show up in the engineering student population. 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 our 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 [25]. Increasing interest in "customer-focused design" [3,4] 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, as those with diverging learning style do. 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 [12,23], 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 counterpart abstract thinkers (those with the assimilating learning style), convergers are action oriented and focus on problem solving rather than problem framing. Unsurprisingly, in our previous study of undergraduate science and engineering students [15], convergers self-assessed their analytical skills to be the strongest among all other skills. For example, we found that students with the converging learning style self-scored high in their ability to “analyze and interpret data” ($p=0.001$). Assimilators, on the other hand, self-assessed their skills in data processing and analysis much higher [15].

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.

Our dataset also raises questions of pedagogy. Schaller et al. [22] 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” [22]. 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 [4]. 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.

While our research suggests that education may need to adapt to different learning styles, and doing so by gender may be relevant, it does not suggest that differentiating education by ethnicity is important.

Finally, our examination of the industry population did not reveal any statistical significance in learning styles across gender. The disappearance of the difference from the student population to the industry population is intriguing. For 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 real world. 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.

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