122nd ASEE Annual Conference & Exposition
June 14 - 17, 2015
Seattle, WA
Making Value for Society
Paper ID #13375

Hybrid Learning Styles

Quintana Clark, Purdue University, West Lafayette

Quincy Clark, a graduate from the College of Technology at Purdue University. Her research interests include emerging technologies for teaching and learning in STEM, e-learning instructional theory and design, and social media as applied to learning styles.

Dr. Alejandra J. Magana, Purdue University, West Lafayette

Alejandra Magana is an Assistant Professor in the Department of Computer and Information Technology and an affiliated faculty at the School of Engineering Education at Purdue University. She holds a B.E. in Information Systems, a M.S. in Technology, both from Tec de Monterrey; and a M.S. in Educational Technology and a Ph.D. in Engineering Education from Purdue University. Her research is focused on identifying how model-based cognition in STEM can be better supported by means of expert technological and computing tools such as cyberinfrastructure, cyber-physical systems, and computational modeling and simulation tools.

Hybrid Learning Styles

Abstract

Several models that predict an individual's preferred learning style have been developed over the last three decades. An individual's learning style is conventionally thought to be categorical into one of a small set of discrete learning style types. Most recently, research based on neuroscience lead to the identification of nine types of learning styles, where each learning style is based on the varying amounts of four learning abilities. In this paper we present results that suggest there exists individuals that have a mixture of two or more of the discrete learning styles. We identify these individuals as having a hybrid learning style. That is, instead of nine discrete learning styles, we suggest that there might be a continuum of intermediate learning styles. If hybrid-learning styles indeed exist, such knowledge might be used to further refine and improve the quality of instruction and learning to a broader audience.

The research question we investigate is: Can an individual possess a hybrid learning style, which is comprised of a distribution of two or more discrete learning styles?

The method we used to determine hybridity is based on Kolb's four-dimensional "kite shape" identifier that is used to categorize learning styles. Each dimension of Kolb's kite shape is a measure of one of four learning abilities. However, instead of quantifying an individual's kite shape to fit into one of nine discrete learning styles, we extend Kolb's work by developing a quantifying threshold, where a kite shape can no longer fit into one of nine learning styles. Such a kite resides at an intermediate location, between two or more of the discrete learning styles. To conduct our investigation, we have created new learning style analysis algorithms that identify and test for this threshold. Our algorithm was administered to 185 university students. Our results revealed that nearly half of the students surveyed had learning style kites that did not fit into any one of the nine discrete learning styles. These results appear to suggest that a significant portion of the population may possess hybrid-learning styles.

Keywords: Hybrid learning style, personalized learning, learning ability

Introduction

Learning styles are preferred learning methods that enable humans to learn more efficiently[1]. When these learning preferences are introduced into a learning environment, they enhance and promote understanding of material, thus creating a positive learning experience[2,3]. Over the last 30 years there has been a call for teaching and learning to embrace a more personalized pedagogy that addresses the individual's learning styles. Personalized learning refers to instruction that is tailored to individual learner preferences and interests[4]. Although effective personalized learning is a difficult challenge it appears to have the potential to greatly increase the numbers of individuals that enter and succeed in the STEM areas of study. For instance, the NAE identified personalized learning as a 21st century grand challenge[5]. Further research and application of hybrid learning styles might contribute to personalized learning.

Background

Cognitive scientists have made significant progress toward understanding how the brain receives and processes information with respect to the learning process[3]. A key question in understanding how one learns is: What facilitates teaching and what hinders learning[2]? Research indicates that learning is a complex convergence of many processes such as student's motivation, teacher instruction, learning material, and several other aspects that interact with each other[3]. Research also indicates that few teachers, especially in higher education, are taught the basis of cognitive science – the learning process[2,6]. As a result, educators are "unfamiliar with the existence of different learning style models and their potential to inform and enhance the learning process or are uncomfortable experimenting with or utilizing learning styles other than their own preference"[3]. This means that educators either teach in a style they prefer to learn, or default to a teaching style that they were taught[2,3]. Either of the two options can interfere with learning and or fail to motivate and promote learning[2,3].

Learning Cycle of Ability

From the field of neuroscience, it was discovered that a "learning cycle arises naturally from the physiological structure of the brain"[7]. The link between neuroscience research and experimental learning theory (ELT) has been suggested in *The Art of Changing the Brain: Enriching Teaching by Exploring the Biology of Learning*[7]. With respect to the brain's structure and the learning cycles, Concrete Experiences (CE) comes through the sensory cortex located at the back of the brain, Reflective Observation (RO) involves the temporal integration cortex at the bottom of the brain, Abstract Conceptualization (AC) happens in the frontal integrative cortex of the brain, and Active Experimentation (AE) takes place in the motor portion of the brain. An illustration of a learning cycle and their correlation to regions of the cerebral cortex is shown in Figure 1. The four phases of the learning cycle are not necessarily sequential as shown. The learning cycle may begin in any one of the four phases. Some phases of the cycle may be passed over.

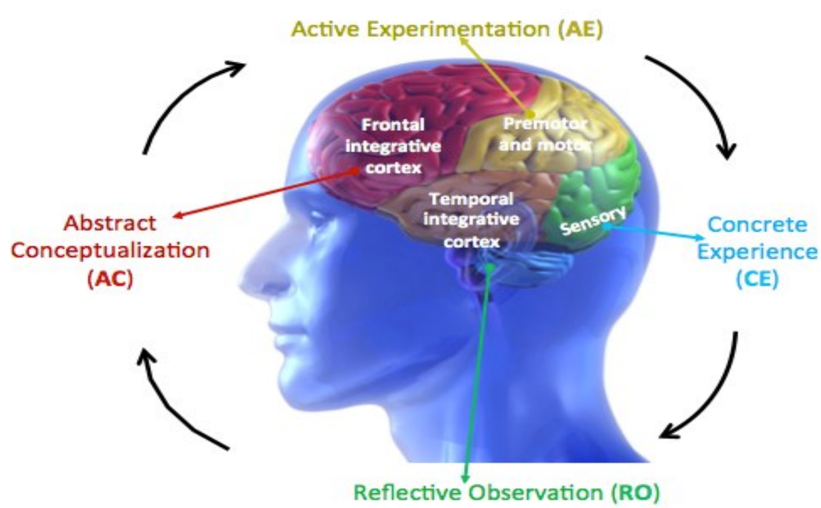


Figure 1: Portions of the experimental learning cycle corresponding to partitions of the cerebral cortex.

There are several learning style models that outline the individual's preferred learning style. Some of the more popular learning style models that are used throughout academia and industry are as follows. The Gregorc Style Delineator (GSD) is based in phenomenological research in that Gregorc defines learning styles as "distinctive and observable behaviors that provide clues about the mediation abilities of individuals and how their minds relate to the world and, therefore, how they learn"[3]. The Dunn and Dunn Productivity Environmental Preferences Survey (or PEPS) defines learning style as "the way in which individuals begin to concentrate on, process, internalize, and retain new and difficult information"[3]. The VARK Questionnaire Fleming model (2001) is a sensory model and is an extension of the neuro-linguistic model[3]. And the Kolb Experiential Learning Theory model (ELT) defines learning as "the process whereby knowledge is created through the transformation of experience"[8]. ELT reflects and extends the theories of notable 20th century scholars: "John Dewey, Kurt Lewin, Jean, Piaget, William James, Carl Jung, Paulo Freire, Carl Rogers, and others"[8]. These scholars developed their theories of learning and development with respect to learning styles with an emphasis on personal experience[8]. From the theories of these scholars, a whole model of Experiential Learning Theories (ELT) was developed[8]. The interplay between the individual and environment creates a conceptual ecology of learning or development spaces. This ecology is composed of the learner's immediate environmental setting such as course work, dorm life or family life, practice of institutional policies and procedures, and involvement in campus culture[8]. It is this ecology of learning spaces that is the theoretical framework for this work on hybrid learning styles.

Kolb and Kolb's conceptual ecology of learning spaces supports the dynamics of learning style and the interplay between an individual's experiences and environment. Decades of research on learning styles, where thousands of individuals were tested, have culminated in the identification of nine types of learning styles: Initiating, Experiencing, Imagining, Reflecting, Analyzing, Thinking, Deciding, Acting, and Balancing[9]. These nine learning styles are defined in Figure 2.

Learning Style	**Definition**
Initiating	Initiating action to deal with experiences and situations
Experiencing	Finding meaning from deep involvement in experiences
Imagining	Imagining possibilities by observing and reflecting on experiences
Reflecting	Connecting experiences and ideas through sustained reflection
Analyzing	Integrating ideas into concise models and systems through reflection
Thinking	Disciplined involvement in abstract reasoning and logical reasoning
Deciding	Using theories and models to decide on problem solutions and courses of action
Acting	A strong motivation for goal directed action that integrates people and tasks

Balancing	Adapting by weighing the pros and cons of acting versus reflecting and experiencing versus thinking

Figure 2: The Nine Basic Learning Styles[9]

These nine types of learning styles are associated with four learning abilities: Concrete Experience (CE), Active Experimentation (AE), Reflective Observation (RO), and Abstract Conceptualization (AC). The learning abilities are defined in Figure 3.

Learning Ability	**Definition**
Abstract Conceptualization	Logically analyzing ideas, planning systematically, acting on an intellectual understanding of the situation
Active Experimentation	Showing ability to get things done, taking risks, influencing people and events through action
Concrete Experience	Learning from specific experiences, relating to people, being sensitive to feelings of people
Reflective Observation	Carefully observing before making judgments, viewing issues from different perspectives, looking for the meaning of things

Figure 3: The Four Basic Learning Cycles of Abilities[10].

Methodology

The research question was: Can an individual possess a hybrid learning style, which is comprised of a distribution of two or more discrete learning styles? Figure 4 illustrates a refined hybrid learning style.

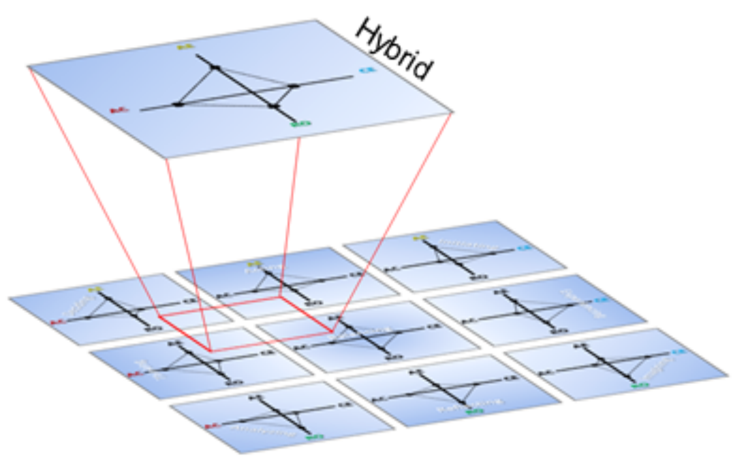


Figure 4: Illustration of a hybrid learning style, which is comprised of a distribution of two or more of Kolb's nine learning styles.

An online *Qualtrics* survey was used to collect learning ability data. The subject matters tested for in our analysis were mathematics and English due to their familiarity and vast differences.

Participants were undergraduate Purdue University students studying a STEM major in the College of Technology. In particular, the participants were enrolled in Tech 12000, Design Thinking in Technology course. The course was comprised of seven sections of about 40 students each. Of the enrolled students N=185. The participants of the study were diverse in gender, age, ethnicity, educational level, and major. The 12 different majors identified were Aeronautical Engineering Technology (AET), Aviation Management Technology (AMT), Building Construction Management (BCM), Computer Graphics Technology (CGT), Computer and Information Technology (CIT), Electrical and Computer Engineering Technology (ECET), Electrical Engineering Technology (EET), Engineering Technology Teacher Education (ETTE), Industrial Technology (IT), Manufacturing Engineering Technology (MET), Organizational Leadership and Supervision (OLS), Professional Flight Technology (PFT), and other. "Other" implied that a major was yet to be chosen.

To improve the chances that participants took the survey, potential survey participants were notified of the survey as an assignment listed on their course syllabus, issued by course section instructors. Participants were given three months to complete the survey. Navigational features of the survey enabled the participants to stop, save, and return to the survey within the three-month period and the option to print a portable document format (PDF) of their completed survey. It was a one-time survey, which did not contain any identifying student information.

The format of the survey consisted of several multiple-choice questions that sought to determine the participant's learning ability. The survey allowed the student to record the level of these abilities by asking indirect questions in various ways that might suggest what ability the participants prefer. The survey asked four pairs of questions, each with four sub-questions, for the two subjects of mathematics and English. Each pair of identical questions was chosen to apply to both subjects.

Each sub-question corresponded to each of the four learning abilities. The multiple choice answers for each sub-question was: (5) Exactly like me, (4) More like me, (3) Less like me, (2) Not at all like me, and (1) Does not apply. Survey participants were allowed to choose any value (1 to 5) for any sub-question.

Our survey methodology was a modification of the Kolb Learning Style Inventory (KLSI) instrument as follows[8]. The KLSI multiple-choice answers did not have a choice of "Does not apply", and identical answers were not allowed. Kolb's inventory instrument used a forced-choice format. For instance, the answer choices of prior research was limited to choosing one answer choice per sub-question that read "Least like you", "Less like you", "More like you", and "Most like you". However, if the test taker's true answer were "Never like you", then a selection of "Least like you" would not accurately capture the participant's true answer. In addition, the participant could not choose the same answer choice for any two sub-questions. Kolb and Kolb's study acknowledged that his force-choice instrument is in contrast to the more normative or free-choice instruments[8]. Although there is ongoing debate in research literature about the merits of forced-choice instruments, Kolb and Kolb's work, The Kolb Learning Style Inventory –Version

3.1 Technical Specifications stated in-part the following about normative or free-choice and ipsative or force-choice survey methodology[11].

> The "pragmatic empiricists" argue that in spite of theoretical statistical arguments, normative and forced-choice variations of the same instrument can produce empirically comparable results. Karpatschof and Elkjaer (2000) advanced this case in their metaphorically titled paper "Yet the Bumblebee Flies[11]." With theory, simulation, and empirical data, they presented evidence for the comparability of ipsative and normative data. Saville and Wilson (1991) found a high correspondence between ipsative and normative scores when forced choice involved a large number of alternative dimensions[11].

Saville and Wilson (1991) stated that ipsative or force-choice "is used for two main reasons: the better control of response sets and to reflect the position that life is about choices[11]." Saville and Wilson (1991) work further discuses the statistical limitations ipsative or forced-choice is inherently subject to[11].

To avoid statistical bias and statistical limitations, thus increasing statistical accuracy of answers, the researcher refined the answer choices to a ranked range free choice format from 1 to 5. Participants were able to choose the same answer for one or more of the sub-questions. A finer distribution of learning styles was expected because the KLSI survey lists 20 questions and each question contained four sub-questions relating to Kolb's four learning abilities (AC, AE, CE, and RO). There were only four forced-choices for each of the four sub-questions, which were "least, less, more and most like you."

An example of the form and type of questions used in the KLSI survey is provided in Figure 5. Each of the four rows in a question set corresponds to a learning ability under test. The four learning abilities are: Abstract Conceptualization (AC) - learning by thinking, Active Experimentation (AE) - learning by doing, Concrete Experience (CE) - learning by experience, and Reflective Observation (RO) - learning by reflecting. Answer choices per set cannot repeat. After an individual completes the survey, levels of learning abilities are computed and fitted onto a template of one of nine learning styles.

In Figure 6 we describe a question set from our Dynamics Learning Style Indicator (DLSI). Similarly, the four learning abilities are under test. The subject matters are integrated into each question, where the questions are strategically chosen such that they likely pertain to each subject.

1. When I learn:	Least like you	Less like you	More like you	Most like you
I like to think about ideas	○	◉	○	○
I like to deal with my feelings	○	○	◉	○
I like to watch and listen	◉	○	○	○
I like to be doing things	○	○	○	◉

Figure 5: One of 20 question sets from the KLSI survey.

Learning Style Inventory Survey		Math: Exactly like me	Math: More like me	Math: Less like me	Math: Not at all like me	Math: Does not apply	English: Exactly like me	English: More like me	English: Less like me	English: Not at all like me	English: Does not apply
1. When I prepare for class…											
AC	…I logically analyze ideas.	5							1		
AE	…I show my ability to get things done.		3						3		
CE	…I leans from specific experiences.					5				2	
RO	…I carefully observe before making judgments.				3				3		
2. When I work in groups…											
AC	…I plan systematically.			2					2		
AE	…I take risks.		4					4			
CE	…I relate to people.	4					4				
RO	…I view issues from different perspectives.	5					5				
3. When I study for exams…											
AC	…I rely on logical thinking.	5					2				
AE	…I work hard to get things done.		3					1			
CE	…I listen and watch carefully.			1							4
RO	…I trust my hunches and feelings.					3					5
4. I learn best by…											
AC	…thinking.				2						3
AE	…doing.		2								3
CE	…watching.				2					5	
RO	…feeling.			1							3

Figure 6: One of 12 question sets from our proposed DLSI survey.

Results

Margin of error (Delta) was determined to measure and plot a students hybrid learning style which can than be determined graphically by plotting a participant's learning abilities to form a kite, and then estimating which ideal kite most closely matched the participant's kite. The shapes of ideal kites are shown in Figure 7.

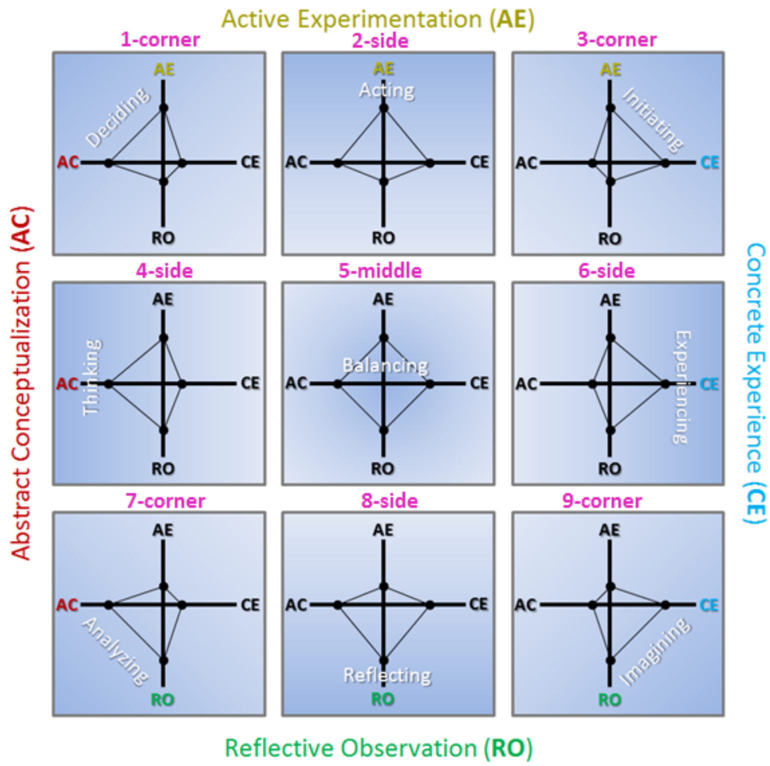


Figure 7: Kite shapes identified as 1-9, and corner, side, or middle[11].

To determine hybridity, each student's delta was compared to the average of all students' smallest delta. The average smallest delta was chosen as the threshold between a hybrid and a discrete Kolb learning style. That is, if a student's smallest delta was larger than the average smallest delta, then the student's learning style did not fit into any one of Kolb's nine learning styles; therefore, the student's learning style was identified as being hybrid.

For example, the ideal kite for the *Balancing* type of learning style has equal levels of learning abilities: AC = AE = CE = RO = 25%. However, a participant that may be perceived as having a *Balancing* learning style may have values of learning abilities that are close, but not quite equal, such as: (AC = 23%) ~ (AE = 25%) ~ (CE = 27%) ~ (RO = 25%). In this case, the smallest margin of error (delta) that can be added to each ability is delta = +/-2%, in order to allow the learning abilities to possibly equal each other. For the *Balancing* learning ability, the algorithm searched for a delta that satisfied: (AC +/- delta) = (AE +/- delta) = (CE +/- delta) = (RO +/- delta). However, in this example, the true values of AE and RO were equal, and the value of CE was greatest and AC was smallest. Now if CE happened to be even larger, and AC happened to be even smaller, then one might presume that the participant's learning style is of type *Experiencing*. So the question was, at what point was the cut-off between a kite that was identified as *Balancing* and a kite that was identified as Experiencing? Figures 8, 9, and 10 show graphical illustrations of how a delta that is too large accommodates more than one learning style and how the smallest delta accommodates only one learning style.

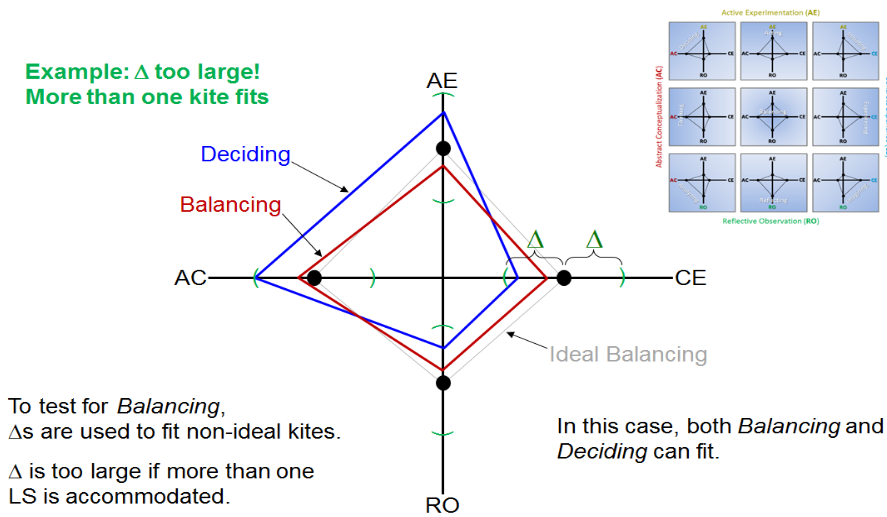


Figure 8: Illustration of a large delta that accommodates more than one learning style kite.

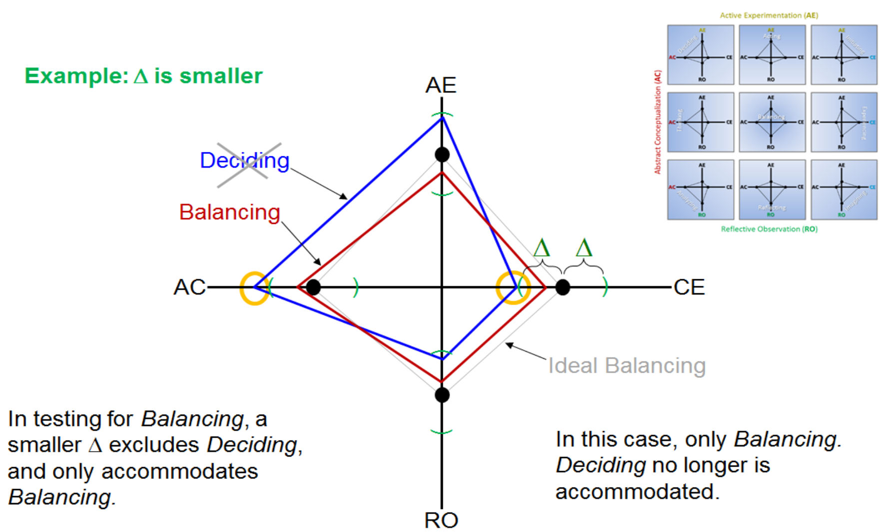


Figure 9: Illustration of a smaller delta thus isolating *Deciding* learning style kite.

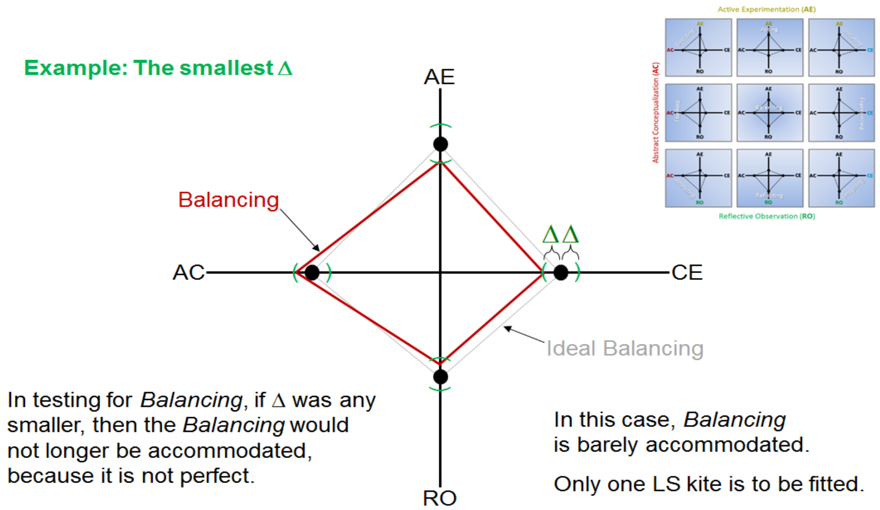


Figure 10: Illustration of the smallest delta possible accommodating only one learning style kite.

The algorithm for determining the smallest margin of error determined the cut-offs by searching for the smallest delta that fit the participant's learning abilities into at most one learning style. If the delta was too large, then a participant might be considered to be all nine learning styles, and if the delta was too small, then a participant might not fit into any learning style.

The algorithm to determine the smallest delta works as follows. Using a Nelder–Mead search algorithm, the smallest delta was found by minimizing an objective function that tests for: existence of learning ability (alpha); a positive delta (beta); and smallest delta[12]. Figures 11 and 12 illustrate how the Nelder-Mead minimization search algorithm was used to determine the objective function that must be minimized to find the smallest delta.

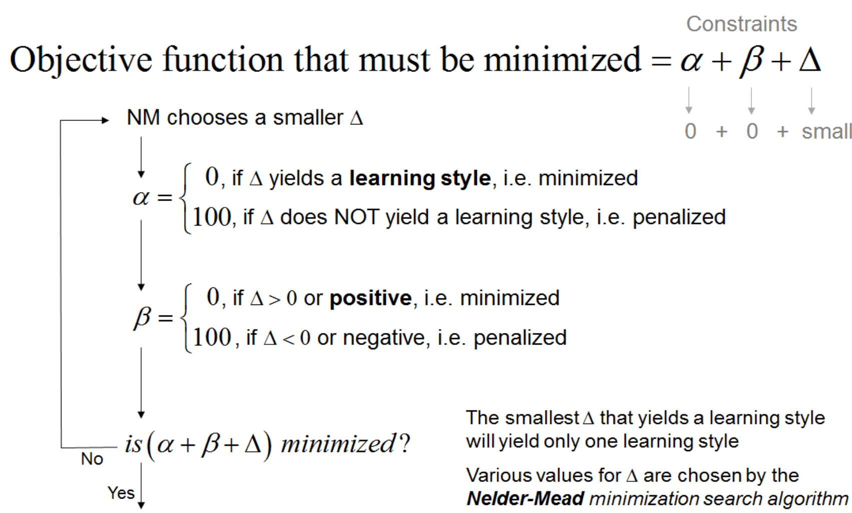
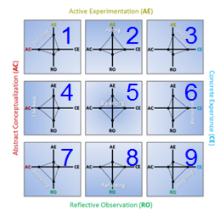


Figure 11: Illustration of how the Nelder-Mead minimization search algorithm minimizes the objective function.

$$middle(AE, AC, CE, RO, \Delta) \Rightarrow 0, \text{or } 5$$
$$corner(AE, AC, CE, RO, \Delta) \Rightarrow 0, 1, 3, 7, \text{or } 9$$
$$side(AE, AC, CE, RO, \Delta) \Rightarrow 0, 2, 4, 6, \text{or } 8$$



$$\alpha = \left(1 - \left[\left(\begin{array}{c}[middle > 0] \\ + \\ [corner > 0] \\ + \\ [side > 0]\end{array}\right) \geq 1\right]\right) \times 100$$

$$\beta = \left[1 - (\Delta > 0)\right] \times 100$$

$$minimize\ (\alpha + \beta + \Delta)$$

Figure 12: Illustration of how the algorithm calculates the smallest delta.

The output of the function was the scalar: alpha + beta + delta. If a learning ability was found, then alpha was 0 (minimized), otherwise alpha was 1 (maximized). If delta was positive then beta was 0 (minimized), otherwise beta was 1 (maximized). Delta should be any real value equal to, or greater than, 0; however, it should be minimized so that the participant's abilities correspond to only one learning style. The search for the smallest delta ended when the objective (alpha + beta + delta) is minimized.

To test the null hypothesis that individuals with hybrid learning styles and individuals with identified Kolb's learning styles were of statistically significant results, independent samples t-test were performed for both mathematics and English results. As seen in Figure 13 the distribution of the deltas were skewed to the right and since neither distribution was normal a KS-test was also preferred. However, a t-test was also used due to its robustness.

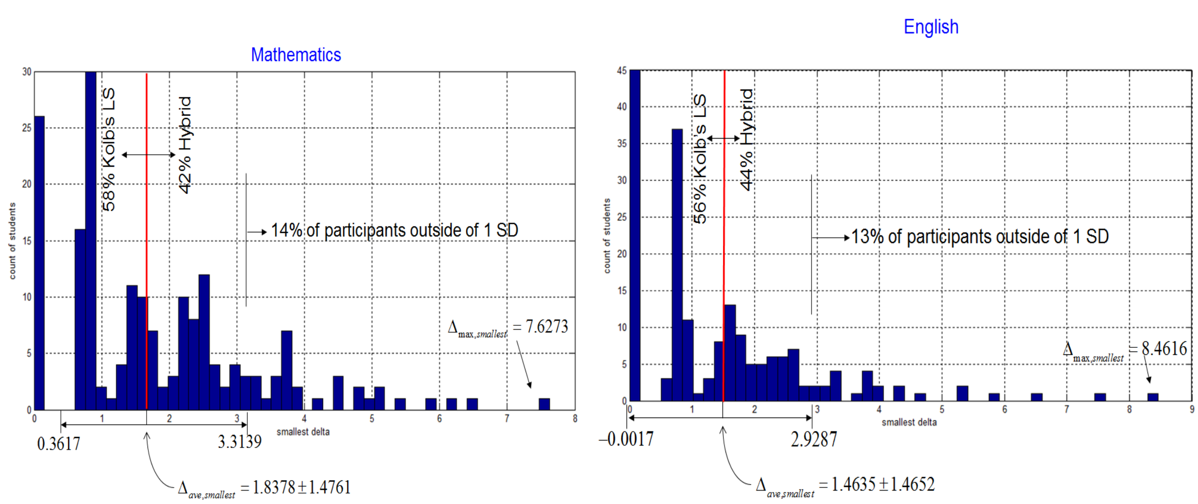


Figure 13: Histograms indicating the deltas for mathematics and English subjects, which are the difference between hybrid learning style kite shapes and Kolb's learning style kite shapes
Hear the researcher determined if the mean of the hybrid learning style deltas were statistically different than the mean of the Kolb learning style deltas. Recall the size of delta determined the difference between hybrid learning styles and Kolb's learning styles. The relationships between sample and delta size for both mathematics and English are shown. The hybrid deltas are to the right of the average delta and the Kolb deltas are to the left of the average delta, where the vertical red line indicates the average smallest delta for mathematics and English.

As shown in Figure 14, the distribution of individuals with hybrid learning styles and individuals with Kolb's learning styles in both mathematics and English were skewed to the right, thus sufficiently normal for the purposes of conducting t-test. Scores were approximately normally distributed with a skewness of 1.052 (SE = .179) and a kurtosis of 1.244 (SE = .355) for mathematics and a skewness of 1.689 (SE = .179) and a kurtosis of 4.178 (SE = .355) for English. P-values for both mathematics and English were p = .000[13].

95% Confidence Interval	Skewness	Kurtosis	Sig. or P-value
Mathematics	1.052 (Std. Error .179)	1.244 (Std. Error .355)	.000
English	1.689 (Std. Error .179)	4.178 (Std. Error .355)	.000

Figure 14: KS-test (normality test) results.

The assumption of homogeneity of variance for both hybrid learning styles and Kolb's learning styles for mathematics and English were tested and satisfied. Mathematics results were t-value = 18.1 and p-value = -000 (1.0933e-042). English results were t-value = 15.4, *and* p-value = -000 (3.8022e-035). The independent samples t-test was associated with a statistically significant effect, where p-value was the probability that a completely random set of data would yield the same results and t-value was the ratio of variance between means divided by the variance within the distributions.

95% Confidence Interval	t	P-value
Mathematics	18.1	-.000
English	15.4	-.000

Figure 15: Independent samples t-test results for mathematics and English (hybridity of learning styles).

Summary

Years of research in the area of learning style preferences have culminated into the identification of nine discrete learning styles. Researchers have also been able to measure the ability of how well a learner may flex between a pair of learning styles. However, prior research appears to stop short of considering the intermediate states between the discrete learning styles, and considering learning style preferences with respect to subject matter.

Personalized learning is one of the fastest growing areas of research and one of the most popular concepts associated with the goals of a 21st century educational system tasked with increasing the nation's numbers in STEM. The National Academy of Engineers (NAE) identified personalized learning as a 21st century grand challenge. This research attempted to contribute to personalize learning concepts by providing evidence for hybridity in learning styles of individuals. Results suggest that a significant percentage of students (greater than 40% of 185) in our sample possessed a learning style that did not fit into any of Kolb's nine learning styles.

A novel survey instrument was created for this study, which enabled students to freely choose which order to answer questions: by learning ability, by pre-question, by post-question, or by subject matter. Results showed that on average the survey was completed in less than ten minutes, which was in many cases 75 percent faster than previous learning style survey instruments.

References

1. Gilbert, J. E., Han, & Han, C. Y. (1999). Adapting Instruction in Search of a Significant Difference. *Journal of Network and Computer Applications 22* (3), 149–160.
2. Brent, R., & Felder, R. M., (2011). How learning works. *Random Thought*, *45*(4), 257-258.
3. Hawk, T. F., & Shah, A. J. (2007). Using Learning style instruments to enhance student learning. *Decision Sciences Journal of Innovative Education 5*(1), 1–19.
4. Atkins, D. E., Bennett, J., Brown, J. S., Chopra, A., Dede, C., & Fishman, B. (2010). Transforming American education: Learning powered by technology. *Learning*, 114, p. 39.
5. National Academy of Engineers of the National Academies, http://www.engineeringchallenges.org/.
6. Felder, R. M., & Spurlin, J. (2005). Applications, reliability and validity of the index of learning styles. *International Journal of Engineering Education, 21*(1), 103–112.
7. Zull, J. E. (2002). The art of changing the brain: Enriching teaching by exploring the biology of learning. Sterling. VA: Styles.
8. Kolb, A. Y., & Kolb, D. A. (2005a). Learning styles and learning spaces: Enhancing experiential learning in higher education. *Academy of Management Learning and Education*, *4*(2), 193-212.
9. Kolb, A. Y., & Kolb, D. A. (2006). Learning styles and learning spaces: A review of the multidisciplinary application of experiential learning theory in higher education. *Learning Styles and Learning* (pp.45-91). Hauppauge, NY: Nova Science.
10. The Kolb Learning Style Inventory 4.0 Personal Report, 2013.
11. Kolb, A. Y., & Kolb, D. A. (2005b). The Kolb Learning Style Inventory – Version 3.1, 2005 Technical Specifications, *Experience Based Learning Systems, Inc. Hay Resources Direct, Hay Group*, 1-71.
12. Mathews, J. H. & Fink, K. K. (2004). Numerical Optimization. In Numerical Methods Using Matlab (4th ed.) (pp. 430-436). Upper Saddle River, NJ: Prentice-Hall Inc.
13. Pallant, J. (2010). *SPSS Survival Manual (4th ed.)*. McGraw-Hill, England: Berkshire.