Learning Style Dynamics

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.

Prof. James L. Mohler, Purdue University, West Lafayette
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.
Learning Style Dynamics

Abstract

Knowledge of an individual’s learning style dynamics might be used to further improve personalized learning, instruction, or educational materials. Previous contributions to learning style theories have assumed that an individual’s learning style preference is invariant. However, the findings in this study suggest that an individual’s learning style preference can dynamically change depending on the circumstances in which the learning is taking place.

A learning style is the type of training method an individual prefers to use in developing working knowledge. We define learning style dynamics as the natural change in preferred learning style as a function of one or more circumstances. Such circumstances might include: type of material being studied, mode of delivery, educational level, motivational level, etc. The particular circumstances that the present study focused on was the type of subject matter.

Related work in this area includes the Kolb Learning Style Inventory (KLSI), which measures learning style and flexibility. Flexibility is the ability of an individual to use a different style than their preferred style of learning. However, one’s ability to change learning styles is not the same as one’s natural change in learning style preference due to circumstances. Since the KLSI survey does not include questions relating to learning circumstances, learning style dynamics does not appear to be measurable by the current KLSI survey.

Based on the apparent assumption made in prior studies, that one’s learning style is invariant to learning circumstances, we chose to test that assumption in this study. We chose the circumstances to be class subjects that all of our survey participants have studied. Our research question was: Can an individual dynamically change learning styles between subject matters (mathematics and English)?

To investigate our research question, we created a Dynamic Learning Style Inventory (DLSI) and analyzed the significance of the results provided by 185 university students. The wording of each survey question was strategically chosen to apply to both mathematics and English to help ensure that differences in learning styles between the disparate subjects were fairly measured. To automate the investigation, we administered our DLSI online and we developed computer algorithms to statistically analyze the survey data. This enables other researchers to verify our findings, perform a DLSI on a different set of individuals, or using a different set of learning circumstances. Our results showed that 36 percent of the students had used a different learning style between studying mathematics and English. These results were shown to be statistically significant ($t_{ave} = 3.39$, $t_{std} = 1.17$, $p < 0.05$), and therefore appear to support the existence of dynamics in learning styles.

Keywords: Learning styles, personalized learning, Learning Style Dynamics, Kolb Learning Style Inventory (KLSI), Dynamic Learning Style Inventory (DLSI)

Introduction

Learning styles are defined as preferred learning methods that enable individuals to learn more efficiently\(^1\). It appears that all humans have learning preferences, although all may not be aware
of their preferences. When these learning preferences are introduced into a learning environment, they enhance and promote understanding of material, thus creating a positive learning experience\textsuperscript{2,3}. Over the last 30 years there has been an increasing call for teaching and learning to embrace a more personalized pedagogy that addresses the individual’s learning style. Personalized learning is defined as instruction that is tailored to individual learner preferences and interests\textsuperscript{4}.

Effective personalized learning is a difficult challenge. For instance, the National Academy of Engineers (NAE) identifies personalized learning as a 21\textsuperscript{st} century grand challenge\textsuperscript{5}. The President’s Council of Advisors on Science and Technology (2012) reported that only four percent of high school students go on to obtain a degree in science, technology, engineering, or mathematics (STEM)\textsuperscript{6}. And less than 40 percent of students pursuing undergraduate degrees in STEM majors completed their program\textsuperscript{6}. The National Center for Education Statistics (NCES) Digest of Education Statistics (2001) reported that of the four million ninth graders in the US, less than half graduated from high school\textsuperscript{7}. And of those high school graduates, one third had no college plans and 56 percent of them were not ready for college\textsuperscript{7}. As Figure 1 illustrates, the study found that the STEM pipeline leaked 96 percent of potential STEM graduates.

![The STEM pipeline](image.png)

Source: NCES Digest of Education Statistics; Science Engineering Indicators 2008

Figure 1: Illustration of the leaky STEM pipeline. Data is from the NCES Digest of Education Statistics & Science Engineering Indicators, 2008\textsuperscript{7}.

Effective personalized learning may have the potential to greatly increase the numbers of individuals that enter and succeed in the areas of STEM. This work stems from prior work based on measuring an individual’s four learning abilities to determine which of nine learning styles they prefer, and an individual’s ability to flex from one learning style to another\textsuperscript{8}. Dynamics may
include how learning style changes with respect to subject matter, type of learning materials, and the style in which the material is being delivered.

A Dynamic Learning Style Inventory (DLSI) survey was developed to query students’ learning ability as a function subject matter. A Qualtrics online survey was used to collect the learning ability data from 185 STEM students from one university. The DLSI data was analyzed using algorithms that were specifically designed to identify and analyze learning style dynamics. Results indicated that 36 percent of the students had used a different learning style between studying mathematics and English, with $t_{ave} = 3.39$, $t_{std} = 1.17$, $p < 0.05$.

The rest of the paper is organized as follows. Background information regarding learning abilities and learning styles are discussed in Section 2. The DLSI survey is presented in Section 3. The learning style dynamics algorithms are overviewed in Section 4. The results are discussed in Section 5. And a summary is given in Section 6.

Background

Learning style models

There are several learning style models that prescribe 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”\textsuperscript{10}. 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”\textsuperscript{10}. The VARK Questionnaire Fleming model (2001) is a sensory model and is an extension of the neuro-linguistic model\textsuperscript{10}.

The Kolb Experiential Learning Theory model (ELT) defines learning as “the process whereby knowledge is created through the transformation of experience”\textsuperscript{8}. Kolb Experiential Learning Theory (ELT) reflects and extends the theories of notable 20\textsuperscript{th} century scholars: “John Dewey, Kurt Lewin, Jean, Piaget, William James, Carl Jung, Paulo Freire, Carl Rogers, and others”\textsuperscript{8}. These scholars developed their theories of learning and development with respect to learning styles with an emphasis on personal experience\textsuperscript{8}. From the theories of these scholars, a whole model of ELT was developed\textsuperscript{8}.

The importance of ELT to this research is that the conceptual ecology of learning spaces supports the dynamics of learning style and the interplay between an individual’s experiences and environment. 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\textsuperscript{8}. It is this ecology of learning spaces that is the theoretical framework for this work on the dynamics of an individual’s learning styles.
The above research on learning styles, where thousands of individuals have been tested, have culminated in the identification of four learning abilities, which are the bases for nine distinct learning styles\textsuperscript{11}.

**Learning abilities and learning styles**

From the field of neuroscience it was discovered that a “learning cycle arises naturally from the physiological structure of the brain”\textsuperscript{12}. The link between neuroscience research and experimental learning theory (ELT) is suggested in *The Art of Changing the Brain: Enriching Teaching by Exploring the Biology of Learning*\textsuperscript{12}. With respect to the structure of the brain and corresponding learning abilities, 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 learning abilities and their correlation to regions of the cerebral cortex is shown in Figure 2, and the four learning abilities are defined in Table 1.

Learning abilities (AC, AE, CE, and RO) may be determined through survey testing. Researchers in this area have led to the founding of Experienced Based Learning Systems, Inc. and related software tools for researching and practicing experienced based learning\textsuperscript{13}. The type of questions used in such surveys are discussed in the next section. After an individual completes the survey, the individual’s levels of learning abilities were computed and fitted onto a learning style template to identify their learning style. Given the measurements of the four learning abilities, one of learning styles may be determined. That is, each learning style can be thought of as a coordinate in a four-dimensional plane, where the axes of the plane correspond to the four learning abilities (AC, AE, CE, and RO). This graphical relationship between the four learning abilities that form the nine learning styles is depicted in Figure 3. Lines connecting the four learning cycles form a four-sided polygon called a ‘kite’. The shape of the kite provides a convenient visual representation of an individual’s learning style. This relationship between ability and style was developed by Kolb and used in the KLSI. The DLSI in this study used the same ability-to-style relationship to determine learning style dynamics. The nine learning styles are defined in Table 2.
Figure 2: Relationship between brain structure and learning ability function\textsuperscript{12}. 3D rendered illustration of head and brain\textsuperscript{14}.

<table>
<thead>
<tr>
<th>Learning Ability</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abstract Conceptualization (AC)</td>
<td>Logically analyzing ideas, planning systematically, acting on an intellectual understanding of the situation</td>
</tr>
<tr>
<td>Active Experimentation (AE)</td>
<td>Showing ability to get things done, taking risks, influencing people and events through action</td>
</tr>
<tr>
<td>Concrete Experience (CE)</td>
<td>Learning from specific experiences, relating to people, being sensitive to feelings of people</td>
</tr>
<tr>
<td>Reflective Observation (RO)</td>
<td>Carefully observing before making judgments, viewing issues from different perspectives, looking for the meaning of things</td>
</tr>
</tbody>
</table>

Table 1: The four learning abilities\textsuperscript{15}.
Figure 3: Relationship between the four learning abilities and the nine learning styles, which form the nine kite shapes\(^{16}\).

<table>
<thead>
<tr>
<th>Learning Style</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initiating</td>
<td>Initiating action to deal with experiences and situations</td>
</tr>
<tr>
<td>Experiencing</td>
<td>Finding meaning from deep involvement in experiences</td>
</tr>
<tr>
<td>Imagining</td>
<td>Imagining possibilities by observing and reflecting on experiences</td>
</tr>
<tr>
<td>Reflecting</td>
<td>Connecting experiences and ideas through sustained reflection</td>
</tr>
<tr>
<td>Analyzing</td>
<td>Integrating ideas into concise models and systems through reflection</td>
</tr>
<tr>
<td>Thinking</td>
<td>Disciplined involvement in abstract reasoning and logical reasoning</td>
</tr>
<tr>
<td>Deciding</td>
<td>Using theories and models to decide on problem solutions and courses of action</td>
</tr>
<tr>
<td>Acting</td>
<td>A strong motivation for goal directed action that integrates people and tasks</td>
</tr>
<tr>
<td>Balancing</td>
<td>Adapting by weighing the pros and cons of acting versus reflecting and experiencing versus thinking</td>
</tr>
</tbody>
</table>

Table 2: The Nine Learning Styles\(^{11}\).
Methodology

Learning style vs. learning circumstance

The purpose of this research study was to investigate the possibility that some individuals change their preferred learning style based on the subject matter being learned. The research question is: Can an individual dynamically change learning styles between subject matters (mathematics and English)? Using this particular learning circumstance as a third dimension, the learning style plane from Figure 3 can extend into this third dimension, where each plane corresponds to the learning style applied to a given learning circumstance. A graphical illustration of learning style dynamics that pertains to this particular study is shown in Figure 4. Our methodology focused on determining which learning style one naturally chooses when placed in the circumstance of learning English (first learning style plane) versus learning mathematics (second learning style plane).

Figure 4: Graphical illustration of learning styles dynamics. Learning style is plotted as a function of learning circumstance. In this particular case, an individual naturally chose an imagining learning style for English, and naturally chose a balancing learning style for mathematics.
Survey

Survey participants were undergraduate students studying a STEM major at a University. The participants were enrolled in a core course open to technology majors. The course was comprised of seven sections totaling 280 students. The DLSI survey was offered as extra credit to motivate participation in this study. A total of 185 students participated in the study by taking the online DLSI survey. The survey was made available to the students through Qualtrics. Navigational features of the survey enabled the participants to stop, save, and return to the survey and the option to print a portable document format (PDF) of their completed survey. They were given three months to complete the survey.

It was a one-time survey that did not contain any identifying student information. Voluntary demographic questions were given at the end of the survey. The participants of the study were diverse in gender, age, ethnicity, educational level, and major.

The format of the survey consisted of several multiple-choice questions that sought to determine learning ability. The survey recorded the student’s 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.

Our survey methodology was a modification of the Kolb Learning Style Inventory (KLSI) instrument. For instance, 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, where the answer choices were limited to choosing one answer choice per sub-question, which read “Least like you”, “Less like you”, “More like you”, and “Most like you”. However, if the test taker’s true answer was “Never like you”, then a selection of “Least like you” would not accurately capture the participant’s true answer. And the participant was prevented from choosing the same answer choice for any two sub-questions. Kolb 2005 study acknowledged that his force-choice instrument is in contrast to the more normative or free-choice instruments. Although there is ongoing debate in research literature about the merits of forced-choice instruments, Kolb 2005 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.

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. Karpatsch and Elkjaer 2000 work advanced this case in their metaphorically titled paper “Yet the Bumblebee Flies.” With theory, simulation, and empirical data, they presented evidence for the comparability of ipsative and normative data. Saville and Wilson’s 1991 found a high correspondence between ipsative and normative scores when forced choice involved a large number of alternative dimensions.

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.” Saville and
Wilson’s 1991 work further discussed the statistical limitations of ipsative or forced-choice is inherently subject to\textsuperscript{18}.

To reduce statistical bias and limitations, we 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).

A closer comparison between the KLSI and DLSI surveys can be seen in Figures 5 and 6. One of the 20 questions from the KLSI survey that was taken by the author of this paper is depicted in Figure 5. And a set of questions given by the present DLSI survey is shown in Figure 6. In both surveys, each row corresponds to the learning ability under investigation. However, in the KLSI, the learning ability rows are randomly chosen, and in the DLSI, the learning ability row is given explicitly and consistently. Each question in the DLSI pertains to both subject matters. Hence, survey participants taking the DLSI have more options on how to navigate through the survey, which ever best fits their survey-taking preference. That is, survey takers are able to answer by learning ability row, by ranking column, by subject matter, or by one question set at a time as in the KLSI. DLSI also allows for identical answers, the N/A option, and the ability to rank the strength of answers. We find that the novel DLSI survey format can be completed at a much faster rate, which can benefit surveys with a large number of questions. That is, there is a nonlinear relationship between the number of questions in a survey and the time spent answering each question. Typically, the more questions a survey has the fewer questions will be answered. The time it takes for a survey to be completed is very relevant to the time a survey respondent will spend answering the questions\textsuperscript{20}.

![Figure 5: One of 20 question sets from the KLSI survey.](image-url)
2. When I work in groups...

<table>
<thead>
<tr>
<th>Style</th>
<th>Statement</th>
<th>RO</th>
<th>AC</th>
<th>AE</th>
<th>CE</th>
<th>RO</th>
</tr>
</thead>
<tbody>
<tr>
<td>RO</td>
<td>I carefully observe before making judgments.</td>
<td>3</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3. When I study for exams...

<table>
<thead>
<tr>
<th>Style</th>
<th>Statement</th>
<th>RO</th>
<th>AC</th>
<th>AE</th>
<th>CE</th>
<th>RO</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC</td>
<td>I rely on logical thinking.</td>
<td>5</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AE</td>
<td>I work hard to get things done.</td>
<td>3</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CE</td>
<td>I listen and watch carefully.</td>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RO</td>
<td>I trust my hunches and feelings.</td>
<td>5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4. I learn best by...

<table>
<thead>
<tr>
<th>Style</th>
<th>Statement</th>
<th>RO</th>
<th>AC</th>
<th>AE</th>
<th>CE</th>
<th>RO</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC</td>
<td>Thinking.</td>
<td>3</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AE</td>
<td>Doing.</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CE</td>
<td>Watching.</td>
<td>5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RO</td>
<td>Feeling.</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 6: Four of 12 question sets from our present DLSI survey.

**Algorithms**

Since the KLSI learning style software was not able to analyze the learning style dynamics, we developed a novel set of algorithms that parsed our DLSI data to identify the nine learning styles, measure the margin of error, measure learning style dynamics, and perform statistical analysis.

An algorithm flowchart of key components of our software is illustrated in Figure 7. As implied by the flow chart, learning style inventory survey data in the form of an NxQ matrix is provided as Survey Input, where N is the number of survey participants and Q is the number of survey questions or answers. Depending on the ranking order of multiple choice questions, some survey tools may enumerate radio choices in the reverse order. In this case, the answer choices of the survey matrix were corrected by using the Identity Reverse algorithm. The survey matrix then passes to the Average Learning Abilities algorithm, which determined the averages for learning abilities for each of the students in each subject. The output of Average Learning Abilities is an Nx4 matrix, where each column corresponds to the average learning ability, i.e., Abstract Conceptualization (AC), Active Experimentation (AE), Concrete Experience (CE), and
Reflective Observation (RO) of each student. The output of Average Learning Abilities is passed to Normalized Percent Learning Abilities, where the survey participant’s learning ability scores were computed into normalized percentages. This was necessary for comparing one student to another. For instance, if one student’s learning abilities (AC, AE, CE, and RO) were ranked 1 1 2 2, and another is ranked 2 2 4 4, then their relative learning ability preferences were virtually equivalent in this study. The output of this algorithm is an N×4 matrix, where the columns are the normalized percentages of learning abilities. The normalized percentage matrix was then passed into the margin of error algorithm that determined the smallest margin of error (Δ) for each student, which was necessary for each student to fit into one of nine learning styles. Last, the results pertaining to learning style dynamics were determined by comparing the learning style of each subject for each student.

Figure 7: Flowchart of algorithms.
Reversal of answer choice ranking was necessary to determine the ranking of learning ability. Here, it was assumed that the higher the rank, the higher the preference to a particular learning ability. Therefore, the learning ability preference data must be properly ranked. If the data was in the opposite order (based on how the survey tool reported its multiple choice answer) then the algorithm ID Reverse algorithm could be used to reorder the ranking into the proper format. The input of the algorithm was the N\times Q matrix. The number of rows were computed and used to determine how many students’ answers needed to be modified. The columns were used to determine the number of answers per student that required modification. The reversal process was done by reversing the answer choices rank order from 5 to 1 to 1 to 5.

The survey queried for learning ability in multiple ways requiring calculation of average learning ability for each student per learning ability. The Average LAS algorithm parsed the data into an N\times 4 matrix of average learning abilities (AC, AE, CE, and RO). The rows correspond to the student and the columns correspond to the four learning abilities. For instance, matrix element (1, 1) was the average AC value for the first student and element (5, 4) was the average RO value of the fifth student. A special case was when a survey participant did not answer a question. The survey tool assigned a value of -99 to that particular answer choice. All participants with a -99 were removed from learning style analysis. The algorithm input was the survey data in matrix form, whereas the algorithm output was an average for each participant’s learning style in matrix form. To account for the answering of some questions, but not all questions, the algorithm only considered answered questions. Averages for each subject were computed separately.

Ratings were converted to a normative percentile based on a total sample of N = 185 ratings from survey participants. The input to the algorithm was an N\times 4 matrix of average learning abilities (AC, AE, CE, and RO). The output was an N\times 4 matrix of normalized percent learning abilities. The code called average for each participant’s learning ability, then converted that average to a normalized percent by dividing each ability (AC, AE, CE, and RO) by the sum total abilities AC+AE+CE+RO, then multiplying by 100 to arrive at the normalized percent.

As discussed previously, learning style can 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 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. Figures 8 and 9 illustrates how the Nelder-Mead minimization search algorithm was used to determine the objective function that must be minimized to find the smallest delta.
Objective function that must be minimized \( = \alpha + \beta + \Delta \)

- \( \alpha = \begin{cases} 0, & \text{if } \Delta \text{ yields a learning style, i.e. minimized} \\ 100, & \text{if } \Delta \text{ does NOT yield a learning style, i.e. penalized} \end{cases} \)

- \( \beta = \begin{cases} 0, & \text{if } \Delta > 0 \text{ or positive, i.e. minimized} \\ 100, & \text{if } \Delta < 0 \text{ or negative, i.e. penalized} \end{cases} \)

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.

Figure 8: Illustration of how the Nelder-Mead minimization search algorithm minimizes the objective function.

Figure 9: 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.
**Results**

**Significance**

To determine dynamics, a comparison was done between Kolb’s nine learning styles of one subject to another subject. If the learning styles of a significant number of individuals were different, then that supported the existence of learning style dynamics. The results of our analysis found that 36 percent (i.e., 67 out of 185 students) used a different learning style between the subjects of mathematics and English.

To test the null hypothesis that at least one pair of learning abilities (AC, AE, CE, and RO) are statistically significantly different for an individual thus indicating dynamics of learning styles, an independent samples t-test was performed. In order for an individual to demonstrate dynamics of learning styles either one of the conditions must be true: \( AC_{\text{math}} \neq AC_{\text{English}} \), \( AE_{\text{math}} \neq AE_{\text{English}} \), \( CE_{\text{math}} \neq CE_{\text{English}} \), or \( RO_{\text{math}} \neq RO_{\text{English}} \). The null hypothesis was therefore \( AC_{\text{math}} = AC_{\text{English}} \) and if \( p \leq 0.05 \) then reject the null hypothesis.

The assumption of homogeneity of variance for both individuals with dynamic learning styles and individuals with non-dynamic learning styles mathematics and English were tested and satisfied. 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. Mathematics and English results were \( t \)-value average = 3.39, \( t \)-value std = 1.17, \( t \)-value maximum = 8.66, \( t \)-value minimum = 2.44 where in order for an individual to demonstrate dynamics of learning styles either one of the conditions must be true: \( AC_{\text{math}} \neq AC_{\text{English}} \), \( AE_{\text{math}} \neq AE_{\text{English}} \), \( CE_{\text{math}} \neq CE_{\text{English}} \), or \( RO_{\text{math}} \neq RO_{\text{English}} \). The \( p \leq 0.05 \) therefore reject the null hypothesis. The results of this study indicated that 36 percent of participants used a different learning style for both mathematics and English, supporting the possibility of dynamics in learning style.

**Selected Demographics**

Demographic data corresponding to the students’ STEM major and gender were analyzed in terms of average learning ability and learning style kite.

Twelve majors were identified in the DLSI survey of 185 participants. These major were: Aeronautical Engineering Technology (AET), Aviation Management technology (AMT), Building Construction Management (BCM), Computer Graphics Technology (CIT), 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). The selection choice of OTHER was an option for students that had not yet chosen a major.

The confidence of the following results depend on the number of students represented the particular major. For instance, we had moderate confidence in the results pertaining to major
OLS with 32 students, and we had no confidence in the results pertaining to major ETTE with only two students. The findings for average learning ability and average learning style kite for each of the twelve majors are shown in Figure 10. The reader may refer to Figure 3 for the relationship between kite shape and learning ability, refer to Table 2 for the definition of learning ability, and refer to Table 3 for the definition of learning style. In Figure 10, the number of students for each major is identified by number N. The six AETs had an average learning style of Balancing for mathematics and Acting for English. Summarizing Figure 10, the nine AMTs had an average learning style of Balancing for mathematics and Thinking for English. The 18 BCMs had an average learning style of Balancing for mathematics and Analyzing for English. The 28 CGTs had an average learning style of Reflecting for mathematics and Thinking for English. The 11 CITs had an average learning style of Balancing for mathematics and Imagining for English. The Nine ECETs had an average learning style of Balancing for both mathematics and English. The Five EETs had an average learning style of Balancing for mathematics and Acting for English. The Two ETTE had an average learning style of Reflecting for mathematics and Balancing for English. The Ten ITs had an average learning style of Balancing for mathematics and Experiencing for English. The 27 METs had an average learning style of Balancing for mathematics and Analyzing for English. The 32 OLSs had an average learning style of Balancing for mathematics and Analyzing for English. And the Four PFTs had an average learning style of Imaging for mathematics and Balancing for English.
Figure 10: Illustration of kite shape of average learning style for each of the 12 identified STEM majors. The numbers next to each learning ability (AE, CE, RO, and AC) equal the percentage of students that identified with that particular learning ability. Also shown are the average learning styles for category “Other” which were identified as several other majors from around campus.

With respect to subject matter, the overall average leaning style for mathematics was Acting and the overall average learning style for English was Initiating, for all majors and genders combined.
Figure 11: Overall average learning styles for both mathematics and English. The numbers next to each learning ability (AE, CE, RO, and AC) equal the percentage of students that identified with that particular learning ability.

Averages learning style kites corresponding to gender are shown in Figure 12. There were 45 were female and 145 were male students. Females had an average learning style of Balance in mathematics and Thinking in English. Males had an average learning style of Analyzing in mathematics and Reflecting in English.
Figure 12: Illustration of kite shape of average learning style per gender. 75% (145) were male and 25% (45) were female. The numbers next to each learning ability (AE, CE, RO, and AC) equal the percentage of students that identified with that particular learning ability.

**Conclusion**

It has been assumed that an individual’s learning style preference is independent of the circumstance under which the individual is learning. Our findings suggest that an individual’s learning style preference can dynamically change depending on the circumstances. In particular, our results showed that a significant proportion of students naturally switch learning styles depending on the circumstance of learning English or mathematics. Of the 185 participants in this study, 36 percent naturally chose to use a different learning style between these two subject matters.

A novel survey instrument was created for this study called the Dynamic Learning Style Inventory (DLSI), which enabled students to freely choose which order to answer questions: by learning ability, by pre-question, by post-question, or by subject matter. We found that the survey was completed at a rate that was much faster than a standard survey format.
Recommendations for further study in learning style dynamics might include other investigating the influence of other types of circumstances, including information delivery mode, motivation level, educational level, and experiences.

Future applications of research in learning style might include identifying an individual’s learning styles as a part of their identity. This might influence ways in which media is presented, such as the format of online learning information such as lectures, reading material, etc. to optimize and improve the quality of learning.

References