Abstract – This paper describes a systematic approach to improving the design of the bioinformatics course by taking advantage of students’ learning styles. Even though the results pertain to introductory bioinformatics modules presented to high school students, the approach is general enough to be applied to effective pedagogy in any area at any level. The design of the course traditionally depends on the available resources as well as the needs of employing organizations. In recent years, however, the focus has shifted to the students’ preparation and the ways in which they learn. Most people tend to be more skilled in some knowledge acquisition abilities than in others. For this reason, students are inclined to favor a particular learning style. It is said that a person’s learning orientation is perhaps the most important determinant of his or her educational attainment. This suggests that we can optimize the module text for a balanced comprehension by the prevalent learning styles observed in the learning population, perhaps by including more visuals or graphics to facilitate intuitive learners and by incorporating formulations and sequencing preferred by analytical learners.

Index Terms – Bioinformatics, Cognitive Style Index (CSI), Intuitive Learning, Analytical Learning, Training.

BACKGROUND

Bioinformatics is the study of the application of computer and statistical techniques to the management of biological information. It is the field of science in which biology, computer science and information technology merge into a single discipline. It employs computers to store, retrieve, analyze and assist in understanding biological information. Specifically, it is the science of developing computer databases and algorithms to facilitate and expedite biological research, particularly in genomics, which includes the development of methods to search databases quickly, to analyze DNA sequences, and to predict protein sequences and structure from DNA sequences.

Bioinformatics requires in-depth knowledge of multiple areas such as statistics, algorithms, mathematics, data mining, natural language processing, genome science, sequence analysis, molecular biology and software programming. The broader goal of our educational project is to help engineering and computer science students get an opportunity to develop skills in computational biology by integrating bioinformatics lecture modules within the existing CSE (computer science and engineering) core curriculum. Our modules cover several application areas such as database searches, sequence analyses, gene expression data analyses, phylogenetic analyses, protein structure prediction, recognition of genes, and so on.

In order to effectively design our modules and develop a “learner-centric” methodology for designing bioinformatics lecture modules, we developed an introductory seminar on bioinformatics to be delivered to high-school students. Our introductory seminar class to high school students runs for one hour and provides an introduction to bioinformatics and biological databases.

An important consideration in the design of educational programs is the learning style of students. Researchers have used a number of different methods of assessing learning styles. Most methods utilize self-report type questionnaires to measure individuals’ approaches to studying and learning. Examples of measures include the Inventory of Learning Process [1,2,3]; the Cognitive Style Analysis [4]; the Learning Style Inventory [5,6]; the Learning Styles Questionnaire [7,8]; and the Cognitive Style Index [10]. Our research utilizes the Cognitive Style Index (CSI) developed by Allinson and Hayes [9,10,11] to measure students’ learning style.

Students were required to complete CSI questionnaires at the beginning of the lecture. After the bioinformatics presentation, an assessment quiz, composed of ten “substantive” questions related to the contents of the presentation, was given. The goal was to determine whether or not quiz performance was related to cognitive style, and if so, would it be possible to remove that dependency through appropriate modifications of the presentation style and enhancement of the seminar content. To view the questions
and presentation modules, you may visit http://asie-lab.secs.oakland.edu/BioInfo.

Using the bioinformatics modules previously developed by faculty who are experts in the field, graduate students made the actual presentations to two groups of high school students aged 15, 16 and 17. For purposes of data analysis, the students were partitioned using a median split into two categories: those with low CSI scores (intuitive learners) and those with high CSI scores (analytical learners).

**Aim**

The aim of this study was twofold. First, to bring about national competitiveness, it is important for university faculty and graduate students to become instruments of change and bring advanced concepts and ideas within the reach of high schoolers. Second, we wished to try out our procedures on a high-school sample. We felt that evaluating the learning of introductory bioinformatics concepts in a sample with less background knowledge in the fields of computer sciences and biology than that found in university samples, could provide a clear measure of students’ ability to learn the novel content within the course module.

Traditionally, the design of a course has been dependent on employing organizations and the limited resources available. More recently, however, the students have become the focus of increased attention, especially their styles of learning. Each developing mind has its own potentiality in achieving knowledge and tends to support a particular learning style. The direction of learning is an essential requirement for the establishment of a person’s educational achievement, and there are various ways to conceptualize an individual’s learning style.

Each person has a preferred sensory modality and mode of expression favoring visual, auditory, or kinesthetic effectiveness [12]. Individuals favoring visual learning, for example, favor perceptions and understanding through image processing in their brain. Those inclining towards kinesthetic learning have the need for hands-on events, such as taking written notes, to maximize comprehension. When describing preferred thinking styles, individuals are serial thinkers or parallel thinkers. Serial thinkers are those who need a proper flow in the concepts they are learning, and parallel thinkers need to see the bigger picture before being able to concentrate on individual concepts. When dealing with such a wide range of learning styles, it is facilitative to involve as much visual, audio and hands-on techniques as possible in teaching; therefore these techniques are the basis for building our presentation modules [13], so that each of the learning modalities is appropriately addressed.

We can compact these learning styles for study purposes to just intuitive (i.e., gestalt or parallel) and analytical (i.e., rational or serial) thinkers. Intuitive thinkers spontaneously go for the first correct answer that comes to them; whereas analytical thinkers strive for a logical reason for answering every question.

There are several methodologies for measurement and assessment of individual learning styles. In our study, we use a cognitive psychological method, the Cognitive Style Index (CSI) developed by Allinson and Hayes to enhance our course content to maximize student learning. This is an interactive process, as shown in Fig. 1.

![Diagram](image.png)

**FIGURE 1**

**PROCESSING INFORMATION FROM CSI: ENHANCING COURSE CONTENT FOR INTUITIVE AND ANALYTICAL LEARNERS.**

Fig 1(a) shows that course material is developed prior to the presentation made to the class. The CSI survey and the assessment quiz are taken before and after the class respectively. Both the CSI scores and quiz results are recorded in a database.

Fig. 1(b) depicts the course enhancement methodology effectuated through the use of CSI scores. As a first step towards that goal, questions where the students performed poorly are identified. Next, we identified whether or not the performance was correlated with learning style. That is, was the performance of analytical learners better or worse than that of intuitive learners.
of the intuitive learners in a statistical sense? If this was indeed the case, our goal was then to enhance the course contents so that performance of both the types of learners can be on par. Thus, if the intuitive students performed poorly, additional graphics and holistic content were added to the course materials. Alternatively, content was enhanced for analytical learners by adding more details, sequence flow graphs and formulae. When performance was uncorrelated with learning style, materials were added to facilitate learning for both the types of learners.

The results presented in the paper are derived from a study of learning styles and performance in 10th and 11th grade high school students from the inner city in the metro-Detroit region. Specifically, we: (1) examine the relationship between age and gender and approaches to learning; (2) examine the relationship between CSI score and quiz score, and (3) begin to establish the soundness of the principles of the approach that we plan to utilize for college students.

METHOD

To begin with, the modules contained as much visual and text material as we felt was appropriate for the topics at hand; namely, two sub-modules providing (i) an introduction to bioinformatics and (ii) bioinformatics databases. Consideration was given to each learning style. Further deficiencies in the module content were analyzed using the CSI as discussed in the later sections. The following slides are illustrative of the general trend.

Figure 2A, shows an example of how a visual “flow” of the definition of “gene” was captured. This slide was well understood by both types of learners.

Figure 2B, explains the usage of the taxonomy database for hands-on try outs. The comprehension of this slide for analytical learners was better than for intuitive learners.

Figure 2C, is one of slides where the students were required to read and parse information that was mostly textual in nature. It has information of the three major databases, the amount of sequences that are transferred between them each day and the introduction of accession numbers. This slide was comprehended well mostly by analytical learners.
As the results later indicate, the intuitive learners like the bigger-picture style learning, while analytical learners can extract fact patterns and relationships from textual content and mentally construct their own semantic relationships and inference mechanisms.

**Measures**

Cognitive style has been defined as consistent individual differences in preferred ways of organizing and processing information and experience. The CSI questionnaire we utilized includes thirty-eight questions, deriving from 18 dimensions identified by Hayes and Allinson. A trichotomous true-uncertain-false response mode was adopted throughout the questionnaire. Some examples of questions are:

- “In my experience, rational thought is the only realistic basis for making decisions” *(analytical style)*
- “To solve a problem, I have to study each of tasks to be performed” *(analytical style)*
- “I find that it is possible to be too organized when performing certain kind of tasks.” *(intuitive style)*
- “I found that to adopt a careful, analytical approach to making decisions takes too long.” *(intuitive style)*

A score of 2 was assigned for a response indicating an analytical orientation, 0 for a response indicating an intuitive orientation, and 1 for uncertain. So the nearer the total CSI score to the theoretical maximum of 76, the more analytical the respondent, and the nearer the total score to the theoretical minimum of zero, the more intuitive the respondent [10].

**Sample**

Twenty-three students predominantly African-American 10th and 11th graders aged 15, 16 and 17, completed both the CSI and the 10 assessment questions. The distribution of our sample in terms of gender and age is shown in Tables I and Table II, respectively. Figure 3 and Figure 4 show CSI score distributions among different genders and ages.

It is interesting to observe that 50% of females are analytical learners, compared to only 33% of males in that category; although as we show later, this difference is not statistically significant. This is a typical pattern for males and females reported in other CSI research.

<table>
<thead>
<tr>
<th>Sex</th>
<th>Intuitive</th>
<th>Analytic</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>6</td>
<td>3</td>
<td>9</td>
</tr>
<tr>
<td>Female</td>
<td>7</td>
<td>7</td>
<td>14</td>
</tr>
<tr>
<td>Total</td>
<td>13</td>
<td>10</td>
<td>23</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Age</th>
<th>Intuitive</th>
<th>Analytic</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>3</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>16</td>
<td>9</td>
<td>7</td>
<td>16</td>
</tr>
<tr>
<td>17</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Total</td>
<td>13</td>
<td>10</td>
<td>23</td>
</tr>
</tbody>
</table>
TABLE III
TESTS OF BETWEEN-SUBJECTS EFFECTS

<table>
<thead>
<tr>
<th>Source</th>
<th>Type III(^2) Sum of Squares(^3)</th>
<th>df</th>
<th>Mean Square(^4)</th>
<th>F(^5)</th>
<th>Sig.(^6)</th>
<th>Eta Squared(^7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>age</td>
<td>382.843</td>
<td>2</td>
<td>191.422</td>
<td>1.789</td>
<td>.197</td>
<td>.174</td>
</tr>
<tr>
<td>sex</td>
<td>8.835</td>
<td>1</td>
<td>8.835</td>
<td>0.83</td>
<td>.777</td>
<td>.005</td>
</tr>
<tr>
<td>age * sex</td>
<td>217.848</td>
<td>2</td>
<td>108.924</td>
<td>1.018</td>
<td>.382</td>
<td>.107</td>
</tr>
<tr>
<td>Corrected Total</td>
<td>1818.900</td>
<td>17</td>
<td>106.994</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Error</td>
<td>2405.304</td>
<td>22</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^2\) Type III model is a fully factorial model that utilizes both the main effects and their interactions.
\(^3\) The Sums of Squares are the total amount of variability in the response; they can be represented by the sum of the squared differences between each observation and the overall mean.
\(^4\) The Mean Squares are the Sums of Squares divided by the corresponding degrees of freedom.
\(^5\) The F Statistic is the ratio of the Mean Square to the Error Mean Square. The null hypothesis that the scores are not different is rejected if the F ratio is large.
\(^6\) The significance is also called p-value, which is the probability of the effect under the null hypothesis.
\(^7\) Eta Squared (\(\eta^2\)) measures the degree of association between the effect (e.g., a main effect, an interaction) and the dependent variable. It may be interpreted as the proportion of variance in the dependent variable that is accounted for by each effect and is as the ratio of the effect variance (VAR\(_{effect}\)) to the total variance (VAR\(_{total}\)). I.e. \(\eta^2 = \frac{VAR_{effect}}{VAR_{total}}\). Thus, it is a measure of the correlation between an effect and the dependent variable.

TABLE IV
PERCENTAGE CORRECT OF EACH QUESTION FOR INTUITIVE STUDENTS AND ANALYTICAL STUDENTS

<table>
<thead>
<tr>
<th>Question</th>
<th>Intuitive</th>
<th>Analytical</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>83.3</td>
<td>72.7</td>
<td>78.3</td>
</tr>
<tr>
<td>2</td>
<td>91.7</td>
<td>90.9</td>
<td>91.3</td>
</tr>
<tr>
<td>3</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>4</td>
<td>75</td>
<td>90.9</td>
<td>82.6</td>
</tr>
<tr>
<td>5</td>
<td>33.3</td>
<td>36.4</td>
<td>34.8</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>36.4</td>
<td>17.4</td>
</tr>
<tr>
<td>7</td>
<td>16.7</td>
<td>9.1</td>
<td>13.0</td>
</tr>
<tr>
<td>8</td>
<td>66.7</td>
<td>63.6</td>
<td>65.2</td>
</tr>
<tr>
<td>9</td>
<td>91.7</td>
<td>81.8</td>
<td>87.0</td>
</tr>
</tbody>
</table>

FIGURE 5: DISTRIBUTION OF QUIZ SCORE FOR INTUITIVE STUDENTS AND ANALYTICAL STUDENTS

Procedure

Prior to the presentation, students were required to complete the CSI survey. Later, after the presentation, the students took a quiz composed of 10 multiple-choice questions related to the subject matter presented.

RESULTS

The CSI score data were first analyzed using SPSS in a 2 (Sex) x 2 (Age) between-subjects Analysis of Variance (utilizing a \(p\) value of <.05). Results are shown in Table III.

Neither age nor gender influenced CSI scores; scores were equivalent for male and female students aged 15, 16, and 17. Next, students were split into two groups, low (intuitive) and high (analytical), on the basis of their CSI scores. One-way Analysis of Variance of learning style on the total score for the 10 test items produced no effects; however, learning style did impact correct answers to question 7, \(F(1,21) = 6.26, p < .03, \eta^2 = .23\). Question 7 asked “As of 2005, how many sequences are contained in the GenBank database”? None of the intuitive students answered the question correctly; whereas over 1/3 of the analytical students did. Percent correct for each of the ten items is shown in Table IV. Figure 5 shows the distribution of quiz scores for intuitive students and analytical students.

The effect on question 7 indicated that we needed to revise the module text for this content area to include more visuals or graphics to facilitate learning by intuitives. In addition, we may need to spend more time on this content area, because the generally low scores suggest that this was a very difficult question for all the students. Two other
questions, #6 (35% correct) and #8 (13% correct), also proved to be extremely difficult, suggesting that these module content areas need to be modified or augmented. Correct responses to the remainder of the test items ranged from 65% to 100%.

**Module Enhancements**

To enhance the modules, we needed to remove the dependency between the learning styles and performance on the questions. Having identified the content corresponding to question 7 (Fig. 2(C)); we added an extra slide in our module to better explain the content assessed by question 7. Fig. 6(a) shows the slide that visually answers the question that appeared problematic to intuitive students. This graphic assists the gestalt thinkers to appreciate the exponential growth of the GenBank database, which appeared to be missed by intuitives in the previous slide shown in Figure 2C.

In addition, we are modifying module content for questions 6 and 8. Fig. 6(b) shows another modified version of the original slide that now “calls out” the description of accession numbers. Students, who miss out on the description of accession number during the lecture, should find the topic easier to remember by the addition of a visual track for memory.

We have not collected follow-up data from the inner-city high school population, but analyses of recent results from university Engineering majors who completed the module in one introductory and one advanced class suggested that the new content for question 7 has removed the decrement in performance by intuitives. In the introductory course sample, the question was answered correctly by 83% of the intuitives and 84% of the analyticals; in the advanced class, 71% of the intuitives and 62% of the analyticals answered it correctly. Learning style did not significantly impact correct responses.

The modified content of the difficult question 6 resulted in much better answers from both classes in the university sample and, as before; learning style did not affect students’ answers. For the introductory class, the percents correct were 65% (intuitives) and 68% (analyticals). For the advanced class, the percents correct were 73% (intuitives) and 69% (analyticals). Question 8 (modified only slightly) was still difficult for the introductory class (52% and 53% correct for intuitives and analyticals, respectively), but much less difficult for the advanced class (71% for intuitives; 85% for analyticals).

**Conclusions**

In this paper we demonstrate how learning styles measured by CSI may be used to enhance teaching effectiveness. Although our study was based on presentation of advanced subject matter to high school students, the ideas presented are generally applicable to instruction at the college levels and to other educational endeavors. In some instances, enhancements may require us to add additional material to provide a holistic view; whereas the modifications needed in other instances may be simply the addition of a callout or selective highlighting to bring forth the broader connotations of the subject matter to assist the gestalt learners. In every case, however, learners’ cognitive styles can help us pinpoint content areas that need attention as well as the type of enhancements needed.

**Acknowledgment**

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**References**


Databases


is the National Institute of Health (NIH) National Center for Biotechnology Information (NCBI) site that contains a number of DNA sequence databases, analysis tools, and numerous reports related to biomedical science.

EMBL and DDBJ are two other major databases, in addition to GenBank. EMBL is in Europe and DDBJ is in Japan. Researchers submit over 30 million sequences and over 40 billion base pairs, and exchange information daily to keep the database in synchronization. This information is organized and retrieved in a “global” system of accession numbers.

FIGURE 6(A): GENBANK GROWTH CHART

FIGURE 6(B): HIGHLIGHTING THE ACCESSION NUMBER