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Original Paper

Implementation of Asynchronous Educational Modules to Improve Student Understanding of Statistical Analysis in STEM Undergraduate Courses

Sophia Barber[1*], Sophia Ibargüen[1*], Chloe Sharp[1], Janet Teng[1], Daisy Kim[1], Richard Luu[1], Jared Ashcroft[1], Yu-Chung Chang-Hou[2]

[1] Department of Chemistry, Pasadena City College, Pasadena, USA

[2] Department of Math & Computer Science, Pasadena City College, Pasadena, USA

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Abstract

Due to the COVID-19 pandemic, many undergraduate students have been given no other option but to take their classes remotely. This has provided many challenges for both students and instructors, especially in the STEM field due to the required laboratory coursework. For this reason, alternative methods of distance learning are needed to optimize student laboratory experiences. The sudden transition to a remote format and adjusting to a new learning environment has proven to be difficult for both students and faculty. It has also been established throughout the pandemic that students perform substantially worse in on-line coursework compared with traditional, in-person classes. Students in a general chemistry course were introduced to innovative asynchronous lab modules that could be performed at home with the additional opportunity of conducting statistical analysis tests. These modules utilize discussion boards, graphing assessments, and labs to teach students how to perform different statistical tests and to familiarize students with the DataClassroom, Google Sheets, and Microsoft Excel platforms. This asynchronous learning format will promote both overall student engagement in STEM courses and student understanding of statistical analysis, thus exhibiting the potential to implement these modules in future undergraduate STEM coursework.

Keywords

statistical analysis, distance education, remote learning environments, modular learning systems, STEM learning strategies

1. Introduction

In early 2020, due to unforeseen circumstances brought about by the COVID-19 pandemic, the entirety of the education system transitioned to a remote format (Aristovnik et al., 2020; Daniel, 2020; Neuwirth et al., 2020). Several studies have supported that remote course formats greatly hinder student learning and content retention (Bashitialshaaer et al., 2021; Barton, 2020; Onyema, 2020; Syafril & Novrianti, 2021; Wester et al., 2021). Such a transition was not only challenging for students who had to adapt to an unfamiliar learning environment, but it proved equally as challenging for educators of all grade levels who were required to develop an online curriculum in a matter of weeks (Bartalesi-Graf et al., 2020; Green et al., Mukhametshin et al., 2021; Parker et al., 2021; Sahu, 2020). As a result, not all concepts previously integrated into course curriculums were seamlessly transitioned to fit this new remote learning format (Dhawan, 2020; Humphrey & Wiles, 2021; Perets et al., 2020). In many STEM courses, without access to a physical lab, the course lab components seemed to suffer exponentially (Hallett et al., 2020; Thomas, 2021; Qiang et al., 2020). Statistical analysis in STEM courses at the undergraduate level, a vital skill required of any prospective STEM professional (Smith et al., 2019; Watson et al., 2020; Watson et al., 2020), serves as an example of one such topic that greatly suffered as a result of losing the in-person laboratory component that made such necessary skills more than abstract concepts and offered students the opportunity to draw connections between their applications and everyday life (Hydorn, 2018).

It is essential to identify solutions that would optimize STEM focused asynchronous learning, especially in terms of improving laboratory coursework in times when in person labs are not available. Asynchronous lab activities that can be performed safely at home without a science laboratory were designed and implemented in a general chemistry course as a supplement to strengthen existing course curricula with a focus on statistical analysis and graphing techniques. These asynchronous modules were developed to increase engagement in distance education, as well as to be employed when in-person laboratories are available. The modules allow students to gain an understanding of the foundation of statistical analysis and why it is crucially important in STEM.

Emphasis was placed on reinforcing students' ability to decipher the major components of statistics, whether that be how to interpret and analyze data or how to perform chi-square and ANOVA tests using a variety of learning platforms. In addition, students were encouraged to participate in peer discussion boards foster soft skills and research skills such as critical thinking, problem-solving, and communication. Once the students developed a familiarity with statistical modules, they then proceeded to the practice of application. Utilizing their novel statistical knowledge and skills, students were provided opportunities to demonstrate their understanding of both basic statistical analysis concepts and practical applications in a series of interactive modules and reflective assessments.

As the skilled technical workforce becomes increasingly reliant on technology, the ability to conduct statistical analysis becomes even more of a necessity for prospective STEM professionals (Ali & Bhaskar, 2016; Enders et al., 2017; Oster & Enders, 2018). Statistical analysis skills can be taught in online courses by utilizing resources on various on-line platforms, such as nanoHUB, an on-line repository of over 1,000 nano-based simulations, which enable professors to implement lectures, simulations, and course material through Canvas. By establishing educational modules that incorporate online-based programs such as DataClassroom and Excel to teach data analysis, students will be better prepared for achieving success within future STEM professions.

Table 1. Student Demographics

Gender	
Male	10
Female	20
Other	0
Prefer not to specify	0
Race/ethnicity	
Asian/Pacific Islander	16
Hispanic/Latino	10
Black/African American	0
White/Caucasian	3
Biracial	1
Other	0
Prefer not to specify	0

2. Methodology

Students were given a pre-course survey and statistical analysis assessment for the primary purpose of establishing a baseline of student statistical analysis knowledge in the General Chemistry and Chemical Analysis II course at Pasadena City College. The responses collected from the assessment and survey played a formative role in the development of the asynchronous modules, allowing them to be tailored specifically to meet the needs of students who come from diverse social and educational backgrounds (Table 1). Students then proceed to work their way through the modules with interactive checkpoints in the form of discussion boards and summative assignments that gauge retention throughout the modules. Once students completed the modules, they took the same statistical analysis assessment to gauge the effectiveness in conveying core statistical analysis topics. The post assessments were analyzed using a matched-pair t-test and the data collected was used to ascertain learning gains in statistical analysis.

3. Program Inputs

In analyzing the pre-modular survey responses, it became apparent that 66% of students enrolled in the General Chemistry and Chemical Analysis II had not taken a statistics course during their undergraduate career (Table 2). In addition, despite the fact that 93% of students enrolled in the course were STEM majors, 85% of the students who had not taken a statistics course had no further plans to enroll in such a class at some point in their undergraduate career. In the same survey, it became apparent that many students were not familiar with commonly used graphing platforms in the STEM field such as Microsoft Excel and Google Sheets (Figure 1). Students also showed a notable lack of familiarity in constructing graphs using Python, which will be addressed in Future Applications.

Table 2. Class Inputs

Student count	30
Percentage of students who are STEM majors	93.33%
Percentage of students who have not taken a statistics class	66.66%
Percentage of students who have not taken a statistics class, and do not plan to take a statistics class	85%

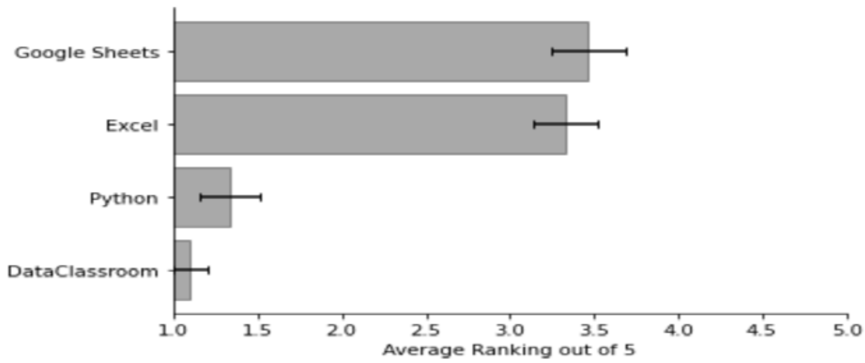


Figure 1. Student Familiarity with Various Graphing Platforms and Techniques. Error Bars Constructed Using ± 1 SEM. N = 30.

While the majority of the class had not taken a statistics course thus far in their undergraduate careers, many students recognized the importance of mastering statistical analysis skills, as they prove vital to the STEM workforce (Figure 2). Surprisingly, although an even greater majority of students indicated that they had no intention of taking a statistical analysis course in their undergraduate careers, 32% of students did indicate on their pre-modular survey that they enjoyed statistics. Within the same line of questioning, students were also asked where they gauged their own statistical analysis skills on a scale of one to five. Unsurprisingly, with 67% percent of students lacking any prior statistical analysis classes, students reported that statistical analysis was not a skill set that they were particularly confident in.

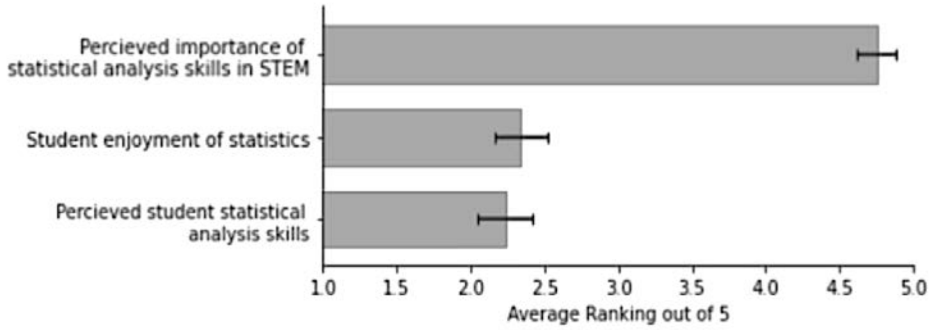


Figure 2. Student Sentiments towards Statistical Analysis. Error Bars Constructed Using ± 1 SEM. N = 30.

The questions that students were given on the pre-modular assessment were based around calculating the mean of a dataset (Q1), calculating standard deviation of a dataset (Q2), defining the term standard deviation (Q3), understanding and distinguishing the difference between a chi-square test, a t-test, and an ANOVA test (Q4), determining when it would be appropriate to use a T-test when given a particular set of data (Q5), and identifying when it would be appropriate to use an ANOVA test when given a particular set of data (Q6). The responses of the pre-modular assessment, which was scored on a scale of zero to five, showed that students had a much stronger understanding of primarily entry level statistical analysis tests but lacked a solid foundation in statistical analysis tests of increasing difficulty (Figure 3).

4. DataClassroom Modules

DataClassroom is an online graphing program that allows students to learn statistical analysis and its significance, especially in scientific and research environments. DataClassroom not only provides streamlined methods for performing statistical tests such as t-tests, ANOVA tests, and chi-square tests, but it also enables students to create detailed step-by-step graphical representations of the statistical analysis methodology to facilitate the learning process even further (Nieves, 2020). By incorporating DataClassroom in Canvas modules, students are given opportunities to practice the data analysis skills that supplement their conventional lectures.

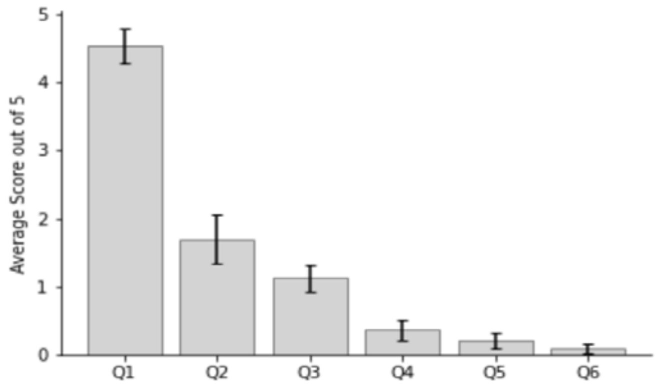
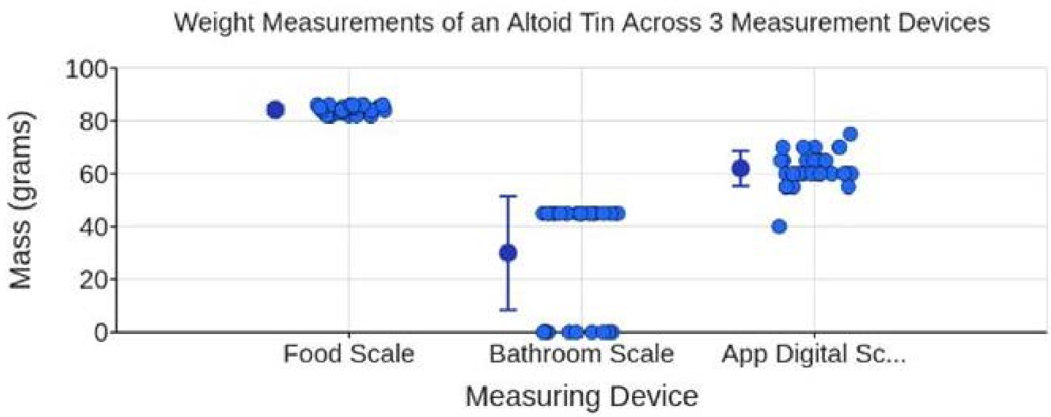


Figure 3. Student Pre-assessment Results. Error Bars Constructed Using SEM ±1. N = 33

Within the modules, students are provided a full introduction to DataClassroom, including both key definitions and video tutorials, and are required to use the DataClassroom platform throughout the modular learning system. Examples of key assignments utilizing this platform include the “Glassware Dry Lab” and the “Food Lab.” These labs aim to replicate the common “Glassware Analysis Lab” taught during in-person courses, providing students with both real data that promotes students’ exposure to common glassware while also teaching the difference between precision and accuracy.

While the “Glassware Dry Lab” is completed in an entirely online setting, the “Food Lab” also promotes student engagement by allowing students to perform the lab in a hands-on setting at home. In this lab, students choose a food and a drink to weigh using three different weighting methods and analyzed which method gave the most precise results and which gave the most accurate results, as compared to the advertised weight on the packaging. While each student had the opportunity to perform the lab in their own kitchen, students also worked remotely with their peers to develop a procedure. Once results were collected and uploaded to a shared document, students were instructed to graph the results in Excel and DataClassroom and write a lab report on their findings (Figure 4). Discussion boards, where students were able to share ideas with the class were also utilized to promote student engagement and mimic a scientific forum.

By completing both the “Glassware Dry Lab” and the “Food Lab,” students developed a foundational understanding of applying statistical analysis skills to real-world problems, developing a proper lab procedure, determining the difference between precision and accuracy, and recognizing the most useful glassware types when attempting to obtain a highly accurate result. In addition, upon completing the modules, students proceeded to utilize their newly acquired understanding of statistical analysis to properly perform chi-squared and t-tests using a given dataset.



Effect	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Squares (MS = SS/df)	F-statistic (MS / MS residual)	P-value	Interpretation of P Explain...
Measuring Device	44540	2	22270	130	<0.01	A P-value of **<0.01** means that the groups are different.
Error or Residual	14850	87	170.7			

Figure 4. Example Scatter Plot and ANOVA Data for the Food Lab

5. Discussion

Once students completed the asynchronous modules, post-survey, and post-assessment, their responses were analyzed to determine whether or not the modules had been effective in increasing students' understanding of statistical analysis concepts. The data collected from these responses showed significant improvement in their scores, particularly in questions two through six (Figure 5). Question one simply requested students calculate the mean of a data set, which is once again considered to be a simpler statistical analysis test to perform. Therefore, it was not surprising that students scored consistently well on this question in both the pre- and post-modular assessments. It is because such a significant increase in students' scores was observed through utilization of a matched-pair t-test that it can be confidently concluded that these modules did indeed help students gain a greater understanding of calculating standard deviation of a dataset (Q2), defining the term standard deviation (Q3), understanding and distinguishing the difference between a chi-square test, a t-test, and an ANOVA test (Q4), determining when it would be appropriate to use a T-test when given a particular set of data (Q5), and identifying when it would be appropriate to use an ANOVA test when given a particular set of data (Q6).

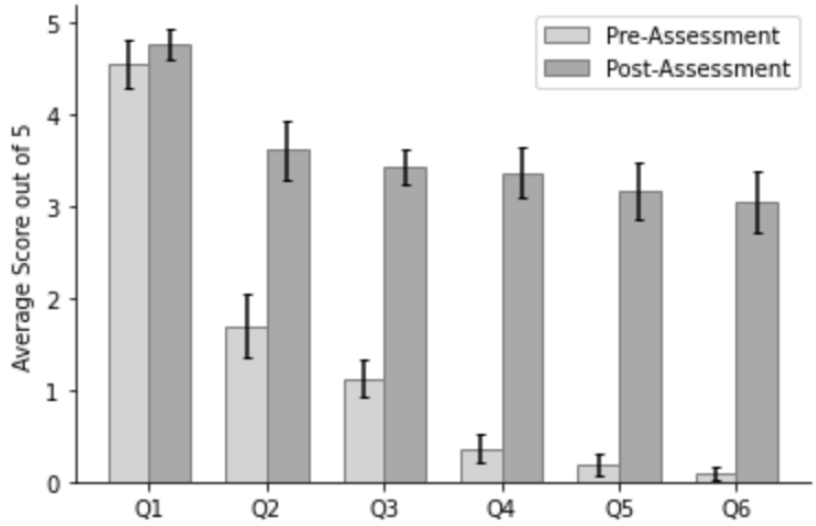


Figure 5. Comparison Pre- and Post-assessment Scores. Error Bars Constructed Using ± 1 SEM. N = 33. Q2-Q6: $p < 0.01$.

In post modular survey responses, students reported an increase in familiarity with all graphing platforms, most notably with DataClassroom (Figure 6). Such an increase was to be expected as the distance education modules provided opportunities for students to practice creating graphs and performing statistical analysis tests in Google Sheets and Microsoft Excel. The notable increase in the students' familiarity with DataClassroom was expected as the modules specifically used this platform. Therefore, in obtaining the desired results, the assertion that the asynchronous modules were effective in their mission to increase students' understanding of statistical analysis concepts and familiarity with useful graphing platforms is supported.

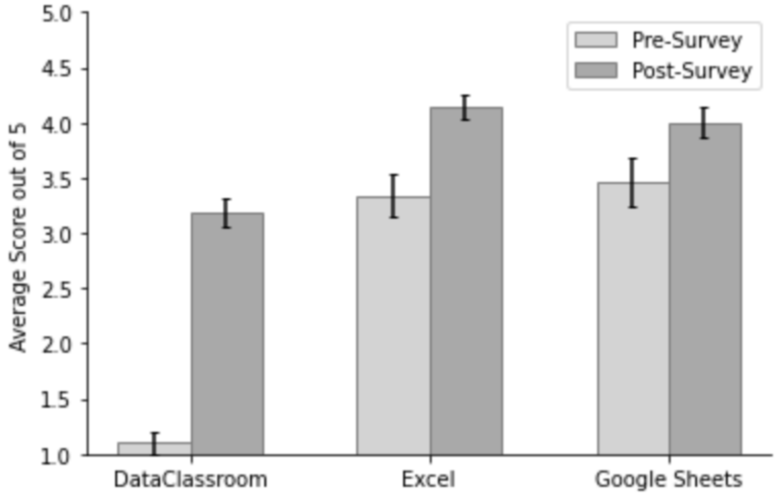


Figure 6. Student overall familiarity with various graphing platforms and techniques. Error bars constructed using ± 1 SEM. N = 30. $p < 0.05$.

Students' overall sentiments towards statistical analysis and their own abilities to effectively exercise their statistical analysis skills also underwent change over the course of several weeks in which the modules were completed (Figure 7). While no statistically significant difference was seen for students' perceived importance of statistical analysis in STEM ($p = 0.586$), this was not unexpected as, even before completing the modules, students ranked the importance of statistical analysis in STEM as 4.6/5, with 5 being very important. Students' confidence in their own statistical analysis skills and their own enjoyment of statistical analysis did show a statistically significant increase, $p = 0.021$ and $p = 0.027$, respectively. These increases in both students' enjoyment of statistics and statistical analysis skills as perceived and studied through assessments, thereby shows the benefits and wide impacts of employing such statistical analysis modules in the distance education classroom.

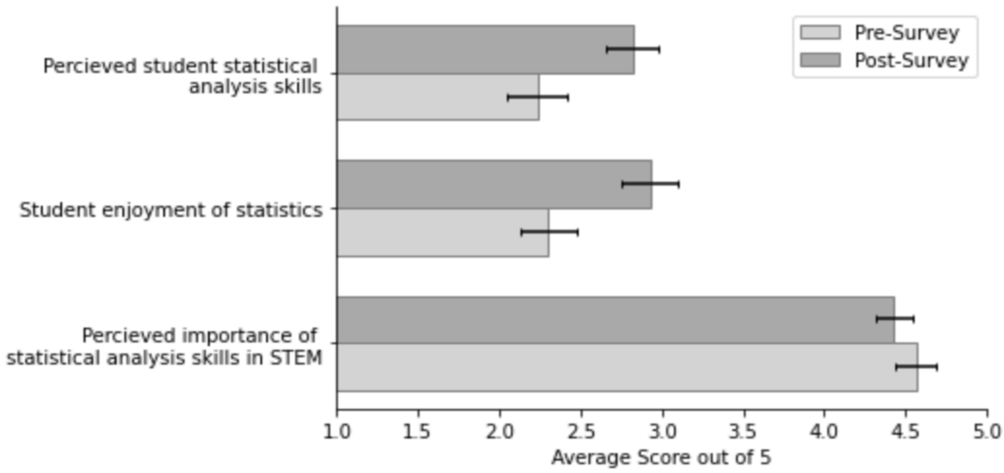


Figure 7. Student overall Sentiments towards Statistical Analysis. Error Bars Constructed Using ± 1 SEM. N = 30. p Values for "Perceived Student Statistical Analysis Skills" and "Student Enjoyment of Statistics" < 0.05.

6. Future Applications

Considering the degree of reliance the skilled technical workforce has on technology, a basic foundational understanding of the programming language Python is also extremely beneficial for students. As a programming language that is applicable in a multitude/diversity of fields, Python allows students to develop computational thinking while also strengthening their problem solving, planning, and procedural thinking skills (Auer et al., 2018; Calderon, 2019; Lee et al., 2017). A Python based statistical analysis module using Google Colab and Jupyter Notebook is currently in development for this reason.

Thus far, the Python module includes an "Introduction to Python" lesson with graphing examples, a survey, and a definitions page. Students then proceed to lessons focused specifically on calculating standard deviation in Python and creating line graphs, swarm plots, and box and whisker plots. While this module is still in its early stages, once completed and implemented into the classroom, students will develop both their statistical analysis and computational thinking skills simultaneously, thus becoming more multi-dimensional candidates for the STEM workforce.

In addition to the Python coding module, a standard curve module will be designed Although the standard curve module was not a part of the original set of modules to teach students statistical analysis skills, after students completed the original DataClassroom modules, a distinct lack in understanding of the standard curve was identified. Because of this, a separate module focused specifically on teaching the standard curve will be created.

Students will first be given a key terms definitions page and several informational videos that teach them how to graph standard curves in Excel and DataClassroom. Students will then be given several assignments and labs, including the “Stolen Painting Mystery” lab, and the “Drink of Choice” lab. The Stolen Painting Mystery lab presents students with evidence left by a thief and requires students to graph and compare multiple standard curves to determine which of the suspects is the thief. The Drink of Choice lab asks students to graph a standard curve to identify an unknown value while also further promoting student engagement by adding a hands-on element that can be performed at home. Throughout both labs, students will continue to participate in discussion boards, allowing them to learn from their peers.

The current state of STEM, where students are assessed on contrived labs meant to give a specific answer are inequitable and geared for success of elite students. There is a clear need to increase success and engagement of all students. The asynchronous, active learning labs described allow students to engage with science, while simultaneously providing an avenue to increase statistical analysis of data. These modules, designed to provide students an authentic laboratory activity during the COVID-19 pandemic education shutdown, will also further increase student outcomes and knowledge with easy infusion into in person labs. Increasing students’ analytical skills and abilities will increase future success in more complex classes and in their future professional career.

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