

2014

Effect of Predicting Motion on Student Understanding of Kinematic Graphs

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EFFECT OF PREDICTING MOTION ON STUDENT UNDERSTANDING OF KINEMATIC GRAPHS

A Thesis

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Master of Natural Sciences

in

The Interdepartmental Program in Natural Sciences

by
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August 2014

Acknowledgements

I would like to thank Dr. Dana Browne first and foremost for taking time out of his already busy schedule to ensure my success in the MNS program at Louisiana State University. His guidance and wisdom have given me more inspiration and insight into physics. You have truly given me hope in physics education. I would also like to thank Dr. Cyril Slezak for the countless hours of guidance with my study. With your help, I feel empowered to do more research and continue to become a better physics teacher. Thank you, Dr. Michael Cherry, for serving on my committee and for the advice provided in making my research more meaningful.

I would also like to thank Dr. Madden for his oversight with the LaMSTI program. This program has been an invaluable asset to my education and has only strengthened my abilities in the classroom. I am also grateful to the National Science Foundation (grant# 0928847) for their funding of such a wonderful program that has brought so many educators in the science community together.

Lastly I would like to acknowledge my LaMSTI cohort, Melanie Dimler, Ann Couch, Zane Whittington, Mary Beth McKenna and Mark Arseneault. Without the daily support and advice we've shared together this program would not have been as meaningful to me.

I would especially like to thank my wife Katie Redding for her encouragement and support during this program.

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Abstract

Different interactive engagements strategies have given students more hands-on involvement in the classroom and helped increase conceptual learning in physics. The purpose of this study was to test the effect of predicting motion graphs by utilizing motion analysis software. Two groups of high school students followed a modified version of Sokoloff and Thornton's seven step ILD process. One group was taught by making predictions. A second group was taught by watching demonstrations. To test for differences in the two groups understanding of kinematic graphs, pre and posttest were taken using the FMCE and Tug-K. The results of both the FMCE and Tug-K showed little to no gains from either the control group or treatment group. Modifying the ILD process and not allowing students the time to discuss their reasoning with other students seemed to be a major factor in the low scores. Although the results of my study are inconclusive compared to other research, there are many immeasurable findings that can help in developing future classroom activities.

Introduction

From the first few months of becoming a teacher, one thing was apparent to me; our students have a difficult time with graphs and data charts. Their difficulties weren't only at a certain grade level but were school wide, and persisted each year. These difficulties were evident in my school's state test scores. The science sections of the tests were mainly charts or graphs where students had to decipher the information. I became curious: why was graphing so difficult to such a broad spectrum of students and what remedy could I implement in my class to correct this problem?

Why do graphs matter anyway? From a scholastic standpoint, they are a part of science and therefore are a part of science class. More importantly, graphs are used everywhere. Every industry and business makes use of graphs in some form (see Figure 1). The news shows trends in world events by using graphs. Weather graphs show us trends in temperature, rain fall and even hurricane patterns. Medical graphs show how new medicines are working to fight different diseases. Every form of business has sales graphs to show if there is actually success in selling what they are producing. Graphs show trends throughout history, political polling data or even engine readings on an automobile or airplane. Graphs are not just a part of science; they are an essential skill to master.

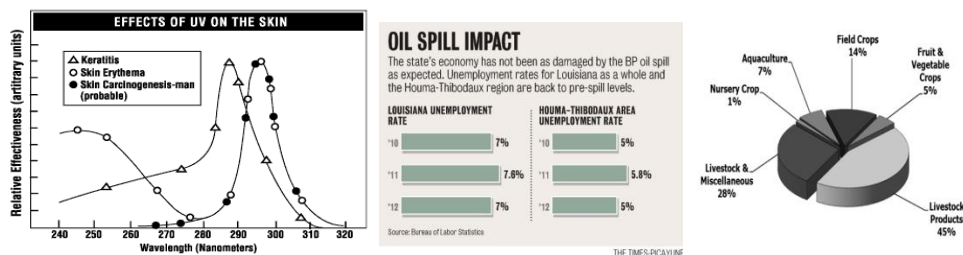


Figure 1: Examples of graphs used in everyday life.

Graphs are a great tool to take a large amount of information and place it in a simple visual display where results can be examined and compared and evaluations made. From bar graphs, line graphs, pie charts to circle graphs, there are many effective ways information can be displayed. We are living in a very technical world today and failure to be able to create or understand graphs can inhibit one's ability for advancement in the workforce.

One example occurred in a conversation I had with a family member. In his job, he began collecting data on sales of different types of outdoor grilling equipment. With graphs he has been able to show that upon purchase of a particular piece of equipment, customers would return on average in three months to purchase additional accessory equipment. He was able to show his employer that they were missing out on numerous other customers also returning to the store. He is responsible for a new web based ordering platform that is now being developed, because he could put together an effective graph.

Why was graphing difficult for my students? It's not that my students couldn't draw a graph. They could manage the mechanical aspects of graphing just fine, namely plotting points and graphing equations. When it came to interpreting complex graphs, drawing nonlinear motion, then their issues become evident. Were the students lacking prior knowledge about these graphs, or was their prior knowledge wrong and hindering their graphing? My first belief seemed obvious; it had to be from previous years of teaching. Students must not have received a proper amount of exposure to graphing. How far back could this lack of understanding go? When do students actually start grouping and plotting numbers together to see an overall picture? What kind and how much work is done at the elementary, junior high and senior high school levels?

Another possible explanation of difficulty seemed to be from teaching in a rural parish. I assumed the vast socioeconomic makeup in our parish had to play a role in the students learning as well. This is one of the poorest parishes in the state of Louisiana. Students have so many other issues facing them than the average house hold income family. Surely there are also numerous other factors that have led to this problem. I can't solve the previous year's problems, fix the poverty level or give every child a descent home environment. I need a curriculum designed to get students engaged in the lesson that has been proven to get results.

For my study I will focus on kinematic graphs in physics. I will observe if my students can recognize an objects motion and draw a corresponding graph. My goal is that students will be better able to understand kinematics graphs by actively engaging in the use of video motion analysis software.

Literature Review

In the last 30 years research has begun to show us that there are considerably better methods of teaching all students to be science minded to some extent. In 1985, Halloun and Hestenes published their research on introductory physics students at Arizona State University. Among their conclusions, they noticed that students have their own preconceived notions about motion and its causes. These preconceived notions have a profound effect on student's performance in class and traditional style teachings do little to correct these beliefs (Halloun and Hestenes, 1985).

One area of student difficulty lies with understating kinematic graphs. Kinematic graphs involve position, velocity or acceleration plotted as a function of time. Morkos and Tinker point out some of the common errors: 1) thinking the graph is a literal picture of the motion. Students tend to think if an object rolls down a bumpy road then the graph will look like a bumpy road, and 2) confusing a large slope of the line with the height of a point on a line. The students believe the largest slope must involve the line with the highest value on the graph. Traditional style teaching does not appear to be solving these problems (1997). Tebaabal and Kahssay also made the point that graphing allows students to use fundamental principles in physics in a nonverbal way. Students taught by traditional lectures fail to learn these fundamental concepts (2011). When these graphical issues are improved, students' conceptual understanding will increase along with their attitudes toward the subject matter (Beichner and Saul, 2014). An example of these misconceptions can be seen in Figures 2 and 3 below. Figure 4 shows one of my student's misconceptions of a graph resembling a picture (graphing problem in Appendix C).

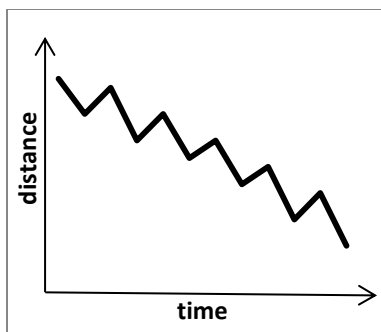


Figure 2: Student perception of a graph of a ball rolling down a bumpy hill.

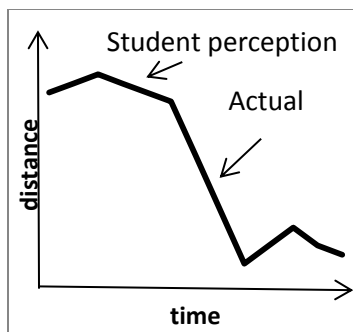


Figure 3: Student perception of highest slope of a line containing highest point.

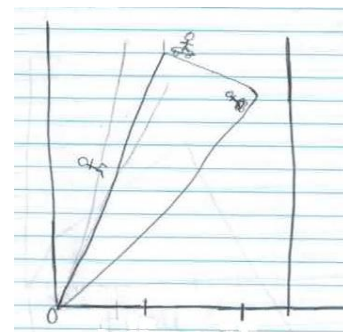


Figure 4: A student graph of a man moving away from a starting point and returning to starting point.

Crouch and Mazur showed that increasing student engagement through discussion is what helps increase student understanding (2001). Students need to be engaged through discussion with peers. Instruction has to become more student centered, rather than lecture centered, to improve graphical skills, kinematic concepts and removal of misconception (Ellis and Turner, 2002). Other researchers have developed their own ‘interactive engagements’ strategies to give students more hands-on involvement in the classroom. They all have the same goal in mind of engaging the student and increasing conceptual learning in physics. David Hestenes’ modeling approach, Eric Mazur’s Peer Instruction and David Sokoloff & Ronald Thornton’s interactive lecture demonstration (ILDs), are all types of interactive engagement. These different methods and strategies help students with misconceptions they have already developed before entering the classroom.

Modeling is a very student centered and student driven method. Students work together to develop their own graphs and make discoveries about physics concepts. While it is great to have students very involved in that process, it does require the teacher to relinquish class control to the students and trust them to be involved. At this point, I am not willing to completely change my daily routine and trust already failing students to lead a group. Another method, Peer

instruction, poses the students with a problem and they work together in small groups to find the answer to that problem. The problems are designed to be engaging and require a discussion amongst the students. While this method has also proven successful, it doesn't have the graphing side that ILDs do. Therefore, I settled on using ILDs in my classroom. ILDs employ extensive graphing, which my students need, and will also help with their conceptual understanding of physics concepts.

In 1989 David Sokoloff and Ronald Thornton put together their ILD strategy that they claim could be used in any size lecture class and would increase student involvement. These ILDs were simple experiments that are used with microcomputer-based laboratory tools (MBL). This was a major focus at the Center for Science and Mathematics Teachings. The development of their curricula has led to changes in learning environments in high schools, universities and colleges. In 1991 a procedure was finalized that could turn traditional (passive) lecture style classes into active ones. The following are the steps to their procedure:

- 1) The instructor describes the demonstration and performs it for the class.
- 2) Students make predictions about the motion and record them.
- 3) In small groups, students discuss their predictions
- 4) As a group, final predictions are recorded
- 5) Instructor repeats the demonstration using the microcomputer-based lab tools
- 6) Final results sheets are filled out by the students
- 7) Different situations are tested on the same concept

It is important to note that the demonstrations accompanied with these steps should be simple and short. Complex demonstrations can lose students understanding and derail the learning process, especially in an introductory class (Sokoloff and Thornton, 1997).

To prove their process worked, in the fall of 1991 a series of ILDs were put to use in a general physics lecture at the University of Oregon. They would cover Newton's First and Second Laws and involve approximately 200 students using pre and post testing with the FMCE. A unit on kinematics was first completed followed by its ILD demonstration, then a unit on Newton's 1st and 2nd law was completed followed by its' ILD demonstration. Each ILD took up about 40 minutes of the usual 50 minute class. Using the FMCE (Force Motion Concept Evaluation), students were tested only on the sections pertaining to the ILDs used, about 21 questions. The results of pre and posttest data show the traditional classes only produced a rise of 7-10% in overall score. In the ILD classes, student average percent score rose to upwards of 80% correct on the posttest (Sokoloff and Thornton, 1997).

Similar results were found in the fall of 1994 when the procedure was repeated at Tufts University. One difference from the Oregon study was that all traditional instruction was carried out before the ILDs were performed. In 1995 the ILDs were integrated into the lecture. Again the average percent score rose from 5-18% correct before ILD instruction to upwards of 80% correct with an integrated ILD procedure. The learning didn't appear to stop here. A final exam given six weeks after the procedures showed no decline in student scores. In fact, there was a 7% improvement (Sokoloff and Thornton, 1997).

In 1990 Sokoloff and Thornton published information about their ILD approach using MBLs. Here they list the characteristics of these tools and why they are important:

- 1) Allow students to choose their direction, making data collecting less time consuming.
- 2) Data is plotted in real-time for immediate feedback.
- 3) Students can make a large number of changes to the data in a single class period.
- 4) The software and hardware tools are able to be used in a variety of experiments.

5) The same set of tools can be used by elementary, high school or college students. However, it must be noted, this tool alone is not enough to produce significant gains. While students enjoy the ability to use computer equipment and manipulate the data, there has to be the right combination with an appropriate curriculum (1990).

Video motion analysis, another form of interactive engagement, was carried out by Robert Beichner to help understanding of kinematic graphs. Using 368 high school and college students, he tested variations in the use of video analysis to see if different levels of integration equate to different levels of scoring. This was accomplished using different teachers from different schools using varying degrees of video analysis integration. The range of class instruction varies from seven different styles. The least interactive was traditional style teaching with neither video analysis nor labs. These involved students at a suburban high school with limited computer resources and a magnet high school. Mid-level interactions include moderate interactive teaching (3 motion analysis labs, students produced their own motion events and no video in the lectures) with college students. High-level interaction included extensive use of video motion analysis, at least half the class sessions. One involved students at a magnet high school, the same school as the least interactive students. Another was college students taught by the author of the study, Robert Beichner, having the most experience with the video motion analysis equipment (1996).

Based on the level of video analysis integration in the seven different groups, mean test scores did increase with increasing integration of the video analysis. Statistical analysis showed there was no difference between these two groups and that simple demonstrations were no more effective than lecturing. The mid-level integration, simply replacing some labs with video analysis labs or simulations, produced a statistical difference in scores when compared to

working in traditional labs. Beichner concludes from this data that the use of video analysis works in different classroom situations and with different styles of teachers. However, used strictly as a demonstration tool does not seem to have an effect. Students must have a variety of ways to be involved with the content while having more hands-on engaging task (Beichner, 1996).

A ten year study was performed by Sharma et al., to research the gains for ILDs. The goal was to produce the same gains, of up to 80%, as in those found from Sokoloff and Thornton's work. When research began, the FMCE was chosen for the measuring instrument, as was the case with Sokoloff and Thornton. Their aim was to determine: (1) could substantial gains with different teachers and levels of students can be achieved? (2) How would their results compare to other studies and other institutions? (3) What were the teacher's attitudes toward interactive learning after using the technique? (Sharma et al., 2010).

The study occurred from 1999 to 2001. Each year students were divided into two groups: advanced and regular. The one advanced group had high school physics and tested high on state-wide exams. The three regular groups also had high school physics but didn't test as high as the advanced group. One regular group of 130 students was chosen as the experimental group, as it was believed they would have the most to gain while also studying at a high level. The other two regular classes and the advanced class would serve as a control (320 students). Over a five week period the classes would have fifteen one hour lectures. Four of the fifteen lectures would be replaced with an interactive ILD. All students involved would take the FMCE before and after their teachings. The following year, 2000, the study was carried out in the same manner and breakdown with each group consisting of similar numbers. Only regular group members were given the pretest out of uncontrollable issues. The third year of the study, 2001,

everything was again carried out in similar fashion with similar numbers in all the groups. The main difference was a new lecturer in the experimental group (Sharma et al., 2010).

The results, according to Sharma et al., show all pretest mean percent scores are roughly the same for the three years, 48%, 55% & 45%. However, there is no quantitative statistical analysis to show whether these numbers can be considered similar or not. For the three years (1999 – 2001), the normalized gains for the control group's scores were, 16%, 13% and 16% respectively. In contrast, the experimental group's gains for those same years were 31%, 50% and 43%, respectively. They note that these gains are significantly larger than the control groups. While the numbers are larger, more than double in some cases, we are not given any statistical analysis to see how or if these numbers are statistically different. They conclude by noting the viability of ILDs in the classroom in improving students understanding (Sharma et al., 2010).

Integration of motion analysis software has made classes more fun for students. Crouch and coworkers (Crouch et al., 2004) wanted to find out if this is just a form of entertainment for the students or is this actually a useful learning tool. Four different groups were examined for this study: (1) a 'control' group, who did not see any demonstrations, (2) an 'observe' group, who saw traditional style demonstrations with teacher explanations, (3) a 'predict' group, where students made predictions about the outcome of the demonstration then listen to the teachers explanations, and (4) a 'discuss' group, where students predict an outcome, see the demonstration, discuss the answer in small groups and then listen to the teacher's explanation. The only other difference in the groups was that the predict group was given a list of multiple choice answers to choose from. The discussion group made predictions based on an open-ended question, then was shown the multiple choice list and chose the closest answer. This study was

performed on 122 premedical students in introductory physics. They had 2.5 hours of lecture a week with a weekly small study session. The study was carried out during the study sessions. An assessment at the end of the semester asked students to make an outcome prediction and give an explanation for their reasoning. Each group was scored by the correctness of their prediction and the correctness of their explanation. Each group's scores were measured individually against the control group. The amount of classroom time used for each group was accounted for separately (Crouch et al., 2004).

While the observe group slightly outperformed the control group in correctness of explanations, the difference was not statistically significant. Simply observing a demonstration was no different than having never seen it. The predict and observe groups each proved to be statistically different from the control group in their explanations on the assessment test. Students being actively involved in the lesson proved significant. Looking at normalized gains for the correctness of outcome predictions, the students that predict the outcome of a demonstration had gains nearly doubled the observation group, 19% to 35%,. When the students are given time to discuss their predictions, their gains rises over the demonstration group from 19% to 47%. As a conclusion students do seem to learn something from traditional style classes, witnessed by the demonstration group. Simply having students make a prediction about an outcome, seems enough to raise their understanding of the underlying material over traditional lectures (Crouch et al., 2004).

Based on this research, I chose to use ILDs to help my students understanding of kinematic graphs. I wish to see if I can modify the seven step process to fit in ten minutes of regular class time and still get similar results as other research. I chose ILDs because I can fit the process into my normal class routine and not have to greatly modify my current style of teaching.

It will also be a strategy that could help my students graphing and conceptual ability. There are other successful strategies being touted today, such as modeling and peer instruction. Neither of these emphasizes the kind of graphing skills that I was interested in studying as well as ILD's apparently did.

Methods and Procedures

The purpose of my research was to observe the effect of students predicting motion on understanding kinematic graphs. To accomplish this I used Sokoloff and Thornton's seven step process on ILDs. This process was modified to fit into the time constraints of my classroom. Instead of devoting an entire class hour, I used the motion analysis software for ten minutes at a time and worked through activities several times a week. This allowed me to still have plenty of class time to go through my regular lesson plans. To demonstrate the motion, each class viewed a video recording of an object in motion. The video motion software tracked this motion and would show a real-time graph being generated as the motion occurred.

Of my two physics classes, one class was arbitrarily chosen to be the control group. They watched the object in motion with the real-time graph being generated at the same time. The other class served as the treatment group. They watch the video of the motion without the graph and then made a prediction of what they thought the motion graph should look like. After their prediction, the video with the real-time graph was shown to check for correctness. Figure 5 shows a comparison of my process the two groups will follow.

Prediction Group (23 students)	Demonstration Group (29 students)
1) Watch motion video	1) Watch motion video
2) Students predict	2) Students predict
3) Predictions discussed	3) Predictions discussed
4) Records final predictions	4) Records final predictions
5) Real-time graph with motion	5) Real-time graph with motion
6) Students record graph	6) Students record graph
7) Repeat:	7) Repeat:

Figure 5: Side by side comparison of the seven step ILD process. Each group is shown with the steps they covered and the steps they did not cover being crossed out.

My study was conducted in a very rural parish in Louisiana. We are also one of the poorest parishes in Louisiana. My school consists of approximately 800 students in grades seven through twelve. We are the only public high school in the parish. This leads to bus riding time of up to two hours in the morning and afternoon for many students. The graduation rate is approximately 65%. Of those graduating, about 55% plan on attending college while the remaining 45% will enter the workforce on their own accord or through some vocational training received at the school. The school has roughly sixty percent eligible for free or reduced lunch. The socioeconomic breakdown is fifty-one percent African-American, forty-seven percent Caucasian and one percent other. The schools socioeconomic breakdown is fairly consistent with the composition on my class. The daily schedule consists of an eight class period day with each class consisting of fifty-four minutes. One class period, sixth hour, is a thirty minute remediation class where students can get additional instruction resulting from having missed school or needing one on one time.

My students consisted of fifty-two high school seniors. This is introductory physics class that these students need for college eligibility. I only had a classroom set of books, so what the students get in class discussion is the only thing they had to take home and study with. The demographic breakdown of the classes is listed in Table 1.

Table 1. Demographic breakdown of my two physics classes.
Total number of students, gender and race.

Group	Total	Male	Female	African-American	Caucasian	Other
Predicting	23	11	12	14	9	0
Demonstration	29	9	20	14	14	1

Both groups spent twenty-five minutes of a class period, before our unit on motion, discussing graphs and how to draw and label the axis correctly. I wanted each group to have a review of how a graph should look and what values are used and on the x and y axis. Once the study began, each student was at a minimum using a correctly drawn graph to plot the motion by the video analysis software.

Each class was given equal time with the motion analysis software and equal exposure to regular class material. The motion analysis software was used at the beginning of a class period for no more than twelve minutes and was used two to three times a week. Each class kept a journal of their graphs in a composition book. An example of a day using the video motion analysis can be seen in Appendix A.

At the beginning of the motion units, the second week of school, each class began work with the motion analysis software twice a week or as much as the school schedule allowed. This took place at the beginning of class for about twelve minutes. The software was only used on days when both groups had at least ninety percent in attendance. During this time the students watched a video of an object in motion. The demonstration group saw the video with a real-time graph of the motion being generated as the object moved. The prediction group was not given access to the real-time graph, they had to predict what that graph should look like. Each group was again shown the motion video with discussion from the instructor about the graph. The study continued to the end of the first semester, finishing our units on motion and forces. The types of motion viewed and the days they were performed are summarized in Appendix B.

The prediction group was taught by making active predictions and having to think about what they were going to draw. The demonstration group did not have to actively think about the graph as they were shown what it should look like.

To test students understanding I used two different assessment test on graphing, the FMCE and Tug-K. Developed by Sokoloff & Thornton, the FMCE is a series of multiple choice questions designed to probe conceptual understanding of Newtonian mechanics. The test makes use of common distractors in the multiple choice problems by listing answers previously given by students on free response tests. The FMCE was administered to both classes on the third day of school (August 21), before any instruction had begun. The FMCE was given again on December 6th, once we finished our unit on forces, to evaluate student gains from the first test. The test administered a third time in April to test for retention of knowledge. The Tug-k was also developed to uncover student difficulties with kinematic graphs. Only questions involving kinematics are used and deliberate distractors are put in to help identify student misconceptions. The Tug-K was administered on September 3rd, after the first unit test but before the motion unit. This test was also given at the end of the semester, December 12th to evaluate student gains from the initial Tug-k.

During the course of this study, I also had the students draw a graph of a specific forward and reverse motion (Appendix C). Both groups were given the same graphing problem three times during the first semester: 1) before the study began, August 22, 2) mid-way through the study, October 15 and 3) end of the study, December 2. The only instructions given were, ‘draw of graph of the motion using any information you think is pertinent to display the motion of the object in the problem’. These graphs would then be compared later to see how students understanding of graphs changes over the course of the study.

Data Analysis and Results

The comparison of data groups in this study was accomplished through the use of 2-tailed T-test. For this study, all of the t-tests were done at a 95% confidence level ($\alpha = 0.05$). The charts I've used for data comparison make use of error bars at the top of each data column. The error bars represent the uncertainty in the mean. I also used normalized gains to compare separate data groups. Normalized gains are a way of 'leveling the playing field' by measuring the difference in pretest to posttest scores divided by the maximum possible score. Other researchers use normalized gains in their data, so I will be able to compare my results to these researchers' data as well. Normalized gains will be found using the following equation:

$$\text{Normalized Gain} = \frac{\text{Posttest score} - \text{Pretest score}}{\text{Perfect score} - \text{Pretest score}}$$

Equation 1: Normalized Gains.

To see if one group had more previous knowledge than the other group, I first evaluated the similarity in my prediction group and demonstration group. This was accomplished by comparing pretest scores on both the FMCE and the Tug-K (Figure 6 & 7) for the two groups. Figure 6 shows the pretest percentage scores on the FMCE, with error bars, to be overlapping enough to be similar. The predicting group's mean percentage score on the pretest was $15\% \pm 1\%$. The demonstration groups mean percentage score on the pretest was $14\% \pm 1\%$. A t-test of FMCE pretest scores confirms this with a p-value = 0.54, the initial data are statistically similar. Figure 7 shows the error bars pretest percentage scores on the Tug-K also to be overlapping enough to be considered similar. On the Tug-K, the prediction group's pretests had a mean percentage correct score of $12\% \pm 2\%$. The demonstration group's pretest mean percentage score was $10\% \pm 2\%$. A t-test of these Tug-K scores confirms the two groups are

statistically the same with a $p\text{-value} = 0.60$. I can now say my predicting and demonstration groups are statistically the same and have similar conceptual knowledge and graphing ability on kinematic graphs before my study began.

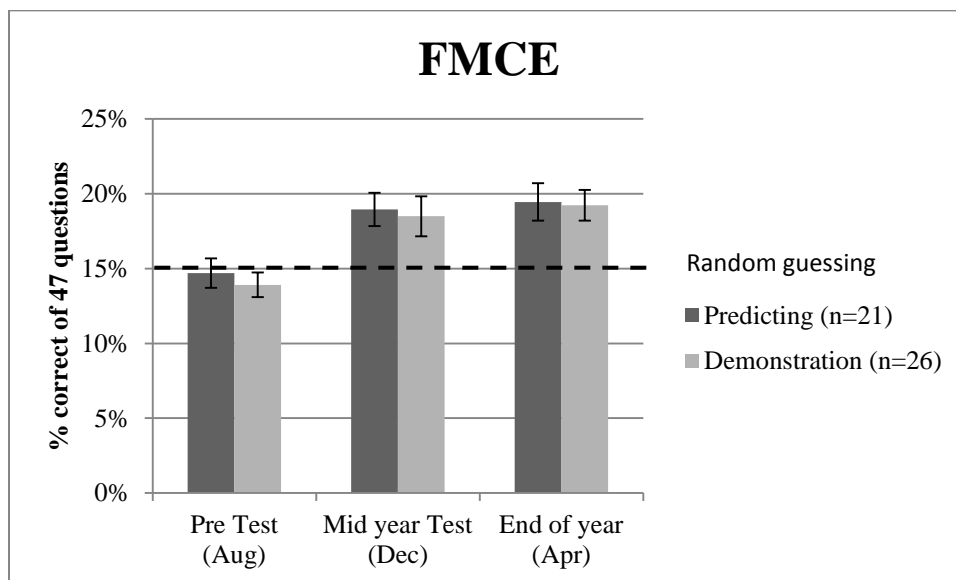


Figure 6: Percentage of correct scores on the FMCE pretest, mid-year test and of year test for the Predicting and Demonstration Groups. A score consistent with random guessing is indicated by a dashed line.

At the end of the first semester (December), both groups were again given the FMCE and Tug-K to test for gains in knowledge. Figure 6 shows the results of the average percentage of correct scores for the FMCE pretest, posttest in December and end of year test. A comparison of the predicting group's posttest scores to pretest scores shows there was a gain in knowledge from the initial test. The prediction group had a posttest score of $19\% \pm 1\%$ and a pretest score of $15\% \pm 1\%$. A $p\text{-value} = 0.006$ confirms a statistical difference. The demonstration group had a posttest score of $18\% \pm 1\%$ and a pretest scores $14\% \pm 1\%$. A statistical difference in scores is confirmed with a $p\text{-value} = 0.005$. Both groups showed a gain in knowledge over their pretest scores.

I also gave the FMCE again as an end of year test in April. During this time no material pertaining to the two assessment tests was covered. From Figure 6, there is no difference in scores from December's test to April's test. The prediction class's end of year posttest has a mean of $19\% \pm 1\%$ and an initial pretest score of $15\% \pm 1\%$. A $p\text{-value} = 0.005$ indicates a statistical difference in the two values. The demonstration group's end of year posttest score of $19\% \pm 1\%$ compared to the pretest score of $14\% \pm 1\%$ gives a $p\text{-value}$ of 0.0002. The numbers indicate that both groups still had a higher understanding over the pretest scores.

Both groups also started out with pretest scores below the random guessing threshold. This does not mean the students can't perform any better than someone who is randomly guessing. They are proving they don't understand the material yet and are performing no better than someone who does randomly guess. By the midyear posttest the test scores did rise above the random guessing threshold.

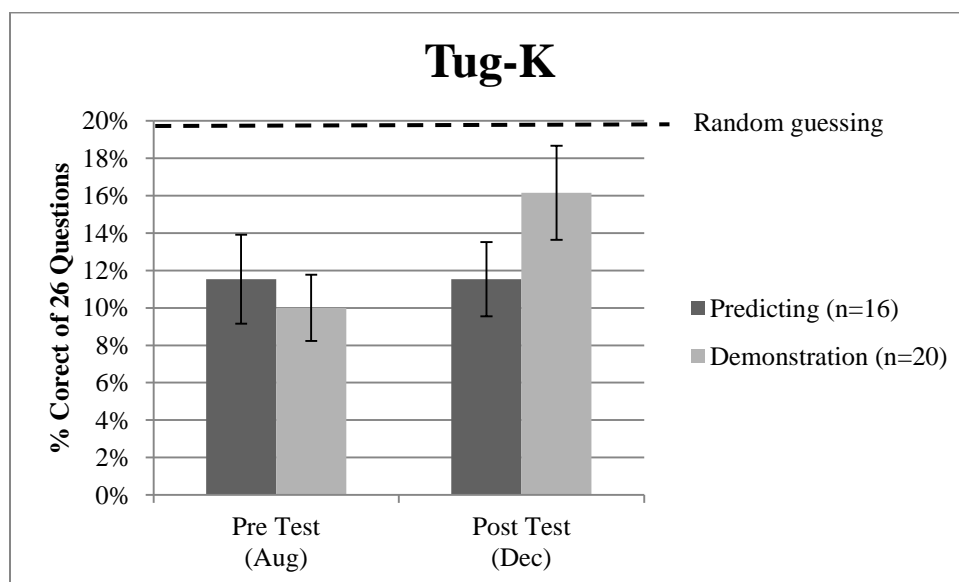


Figure 7: Percentage of correct scores on the Tug-K pretest and posttest for the Predicting and Demonstration Groups. A score consistent with random guessing is indicated by a dashed line.

Figure 7 gives the results of the average percentage of correct scores for the Tug-K pretest and posttest. The predicting group had a mean percentage pretest score of $12\% \pm 2\%$. The posttest score for the predicting group was also $12\% \pm 2\%$. A p-value = 1.0 for the predicting group confirms there is no statistical difference from pretest to posttest. The demonstration group had a mean percentage pretest score of $10\% \pm 2\%$ and a posttest score of $16\% \pm 3\%$. These scores have a p-value = 0.053 for the demonstration group, confirms that there is no statistical difference. On the Tug-K neither group did any better on the posttest than they did on the initial pretest.

The percentage of correct scores for both group's pre and posttest on the Tug-K is noted to be significantly below the random guessing threshold. Again, this does not indicate the students are bad at random guessing but that they are holding on to an incorrect belief as to what the right answer is. I believe my students are still holding on to some misconception in graphing and it is keeping them from picking the correct answer. I could be that they are looking for an answer resembling a picture of the motion. They may not even understand what the questions are asking them to find.

Figure 8 gives a comparison of the normalized gains for on the FMCE for the predicting and demonstration groups. The predicting group had a normalized gain of $5\% \pm 1\%$ and the demonstration group normalized gain was $5\% \pm 2\%$, so no statistical difference is apparent. The gains are also significantly lower than the 80% gains obtained by Thornton and Sokoloff (1997) or even the 31-50% gains from Sharma et al. on the FMCE (2010). Their use of the full ILD process, with discussion, seems to be an important step. I am also not teaching college level students. My students are in a very rural public high school.

Figure 8 shows a comparison of the normalized gains experienced on the Tug-K for the predicting and demonstration groups. The predicting group's normalized gain was $-1 \pm 3\%$ and the demonstration group gain was $7\% \pm 2\%$. A p-value = 0.057 indicates that there is no statistical difference in the two groups.

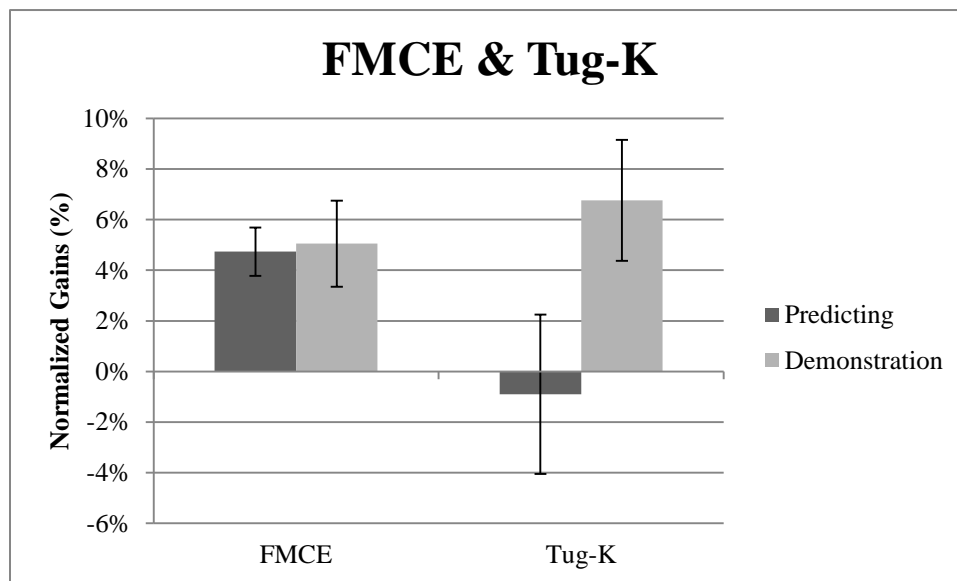


Figure 8: Average percentage of normalized gains on the FMCE and Tug-K for the Predicting group and Demonstration Group. FMCE: n = 21 predicting and n = 26 demonstration. Tug-K: n = 16 predicting and n = 20 demonstration.

I also wanted to see if I could detect any gender differences in these results. According to Lorenzo et al., (2006) the gender gap should get smaller with increased student engagement.

Figure 9 shows the difference in gender scores for the prediction and demonstration group on the FMCE. All the statistical values for these groups are listed in Table 2. Pretest scores in both groups seem higher for the females in each groups pretest than the males. Research data suggest that males generally score 13% higher on pretest scores than females on mechanic based test like the FMCE (Madsen et al., 2013). In the predicting, group a t-test between the females mean score $17\% \pm 1\%$ (pretest) and the males mean score $12\% \pm 1\%$ (pretest), has a p-value = .01.

Contrary to other research, these females have higher pretest scores than the males. We are only

dealing with a sample size of around ten for the males and females in the predicting group, so these differences may not be significant.

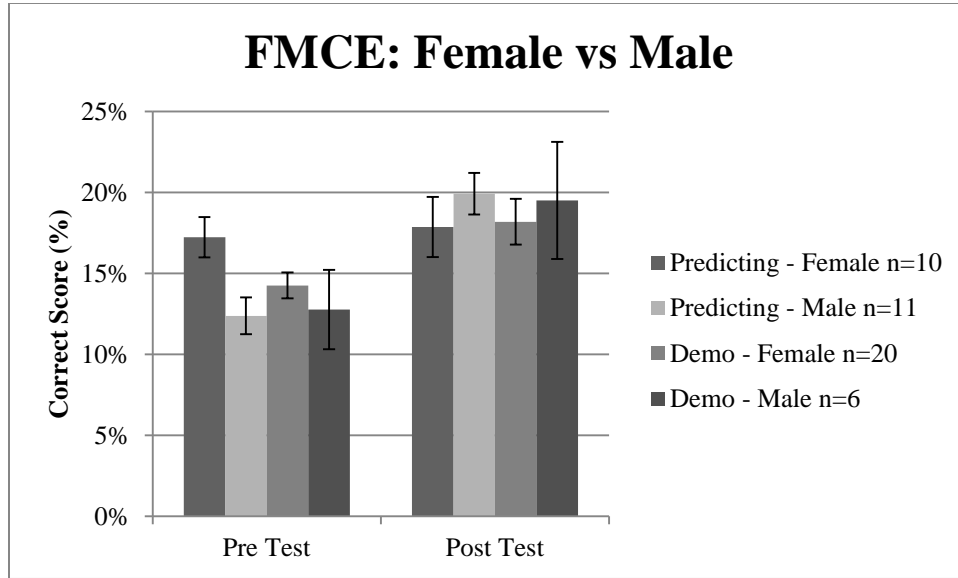


Figure 9: Female and Male percent scores on the FMCE. Pretest and posttest scores are given for each gender in the Predicting and Demonstration groups.

Table 2: Statistical values for FMCE scores for males and females.

FMCE		Males			Females		
	Statistical value	pretest	posttest	N-gains	pretest	posttest	N-gains
Predicting	Mean	12%	20%	8%	17%	18%	1%
	Standard Deviation	4%	4%	6%	4%	6%	8%
	Count	11	11	11	10	10	10
	Uncertainty	1%	1%	2%	1%	2%	3%
Demonstration	Mean	13%	20%	8%	14%	18%	4%
	Standard Deviation	6%	9%	10%	4%	6%	8%
	Count	6	6	6	20	20	20
	Uncertainty	2%	4%	4%	1%	1%	2%

Posttest scores were also compared. Research suggests that the gender gap on posttest scores is approximately 12% on mechanic based test, such as the FMCE, FCI or MBT (Madsen et al., 2013). In this study all posttest scores are similar in value. The only significant increase over the pretest came from the males in the predicting group. These males had a posttest score of $20\% \pm 1\%$ and a pretest score of $12\% \pm 1\%$. A p-value = 0.0003 shows these scores to be significantly different. An ANOVA was also performed on the two groups. The pretest ANOVA gave a p-value = 0.048, indicating a difference in the groups. The ANOVA for the posttest scores gave a p-value = 0.8, indicating no difference. I must emphasize that in this data we are dealing with a very low sample population. Trying to make statistical sense with sample sizes of six or ten is not going to be very fruitful.

A comparison (Figure 10) of normalized gains for the genders for each group shows the only significant gain came from males in the predicting group, $8\% \pm 2$, over the females in the predicting groups, $1\% \pm 3$. This is confirmed with a p-value = 0.02. However, we are again dealing with very low sample sizes. This 6% gain is where Madsen et al. list the gender gap for mechanic based test such as the FMCE, FCI or MBT (Madsen et al., 2013). These sample sizes are so low the 6% difference may not be real. All other comparisons of gains are statistically the same. One gender does not stand out from the others in any group in terms of gains on the FMCE.

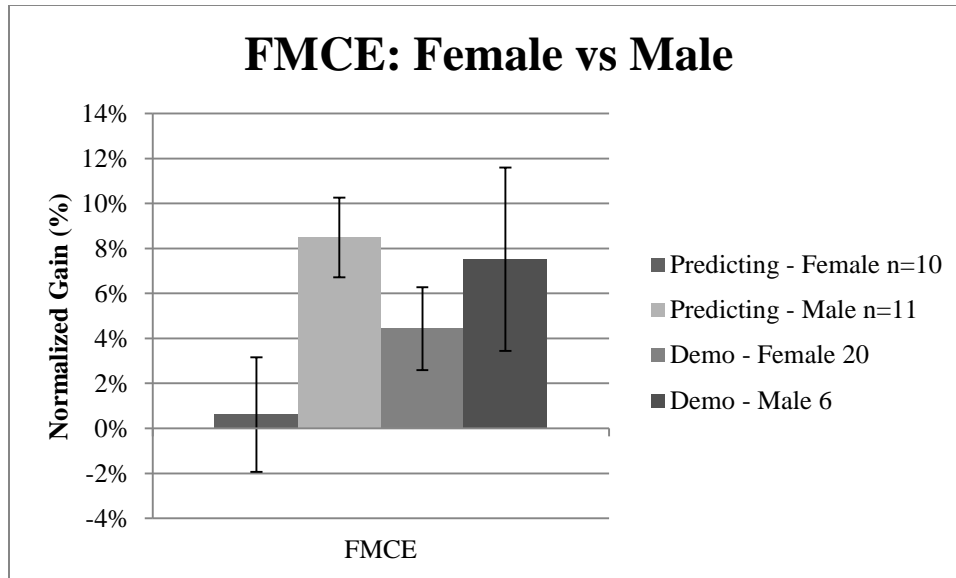


Figure 10: Normalized gains on FMCE broken down by gender.

Figure 11 gives the gender breakdown for the two groups on the Tug-K. The comparison of pretest scores shows that all groups can be considered as similar. No difference exists from the male groups to the female groups. The posttest results show no statistical gains over the initial pretest either. However, a t-test shows that there is a difference in the posttest scores of the both male groups over the predicting female group. Beichner's (1994) study points out that males generally do statistically better on the Tug-K than females (mean scores of 9.5 for males compared to 7.2 for females, after instruction). I find it interesting that both groups of males outperformed the predicting females and not the demonstration females. However, we are again dealing with an extremely small sample size for differences to be considered significant. A comparison of normalized gains for these groups can be seen in figure 12. All comparisons between the groups and genders result in p-values > 0.05 . Neither gender in either group did any better than another group on the Tug-K. A listing of all statistical values for the Tug-K gender breakdown is in Table 3.

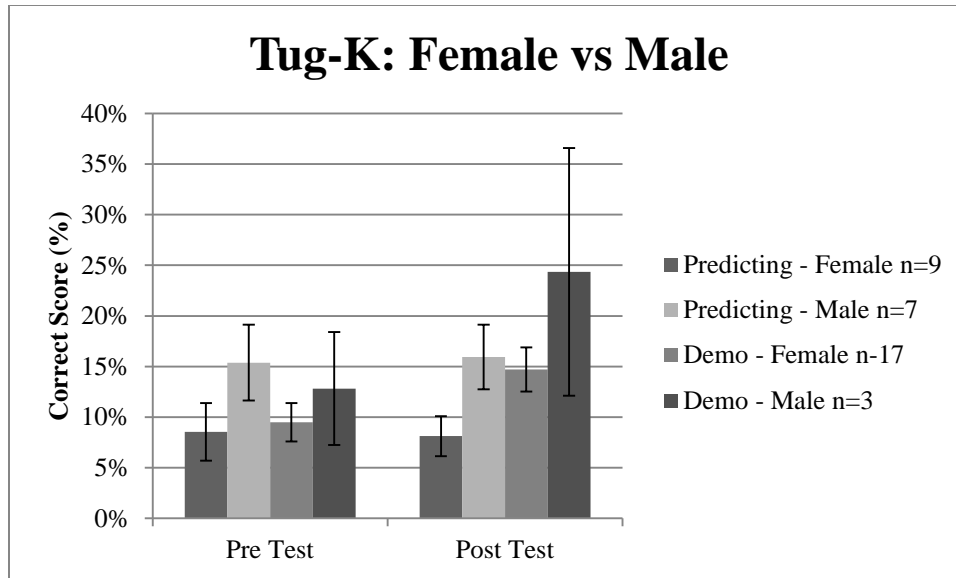


Figure 11: Female and Male percent scores on the Tug-K. Pretest and posttest scores are given for each gender in the Predicting and Demonstration groups.

Table3: Statistical values of Tug-K scores for males and females.

Tug-K		Males			Females		
	Statistical value	pretest	posttest	N-gains	pretest	posttest	N-gains
Predicting	Mean	15%	16%	0%	9%	8%	-1%
	Standard Deviation	10%	8%	12%	9%	6%	14%
	Count	7	7	7	9	9	9
	Uncertainty	4%	3%	4%	3%	2%	5%
Demonstration	Mean	13%	24%	14%	10%	15%	5%
	Standard Deviation	10%	21%	15%	8%	9%	10%
	Count	3	3	3	17	17	17
	Uncertainty	6%	12%	9%	2%	2%	2%

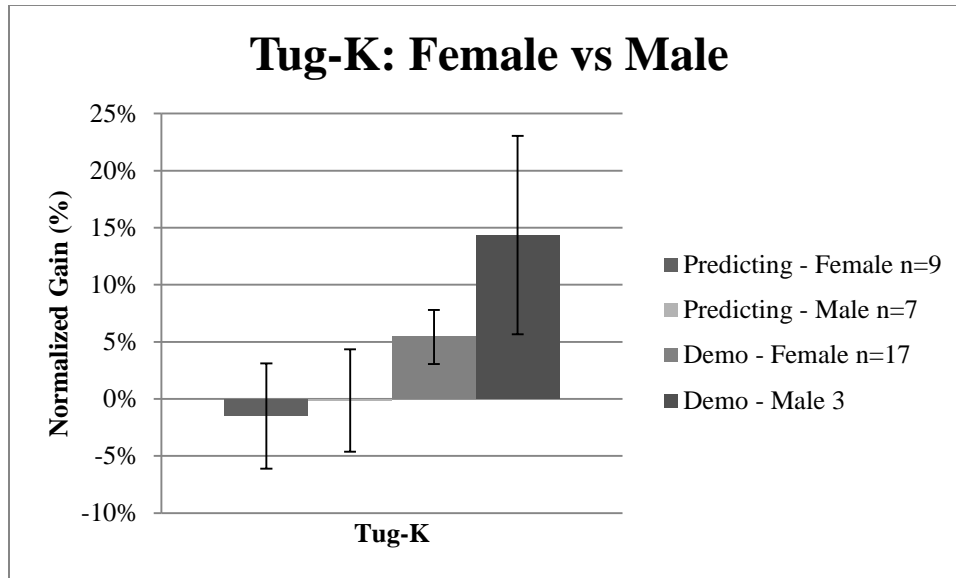


Figure 12: Normalized gains on Tug-K broken down by gender.

To see if perhaps there was any one section of the FMCE that a group may have excelled in, the test was broken down among the different test categories. The categories and the results of that breakdown are shown in Figure 13. The results do not show that there was any one section a group tested on better than another. All categories for both groups are similar in their amount of gains, which is also small. We are still dealing with a very small sample population, so any differences in figure 13 should not be considered significant. The statistical values of the different categories on the FMCE are listed in Table 4.

An item analysis of the Tug-K was also done to check the group performance in each section (figure 14). The results of this breakdown are again inconclusive. Any differences in gains are not significant due to the very small sample population. All statistical values of the breakdown on the Tug-K can be seen in Table 5.

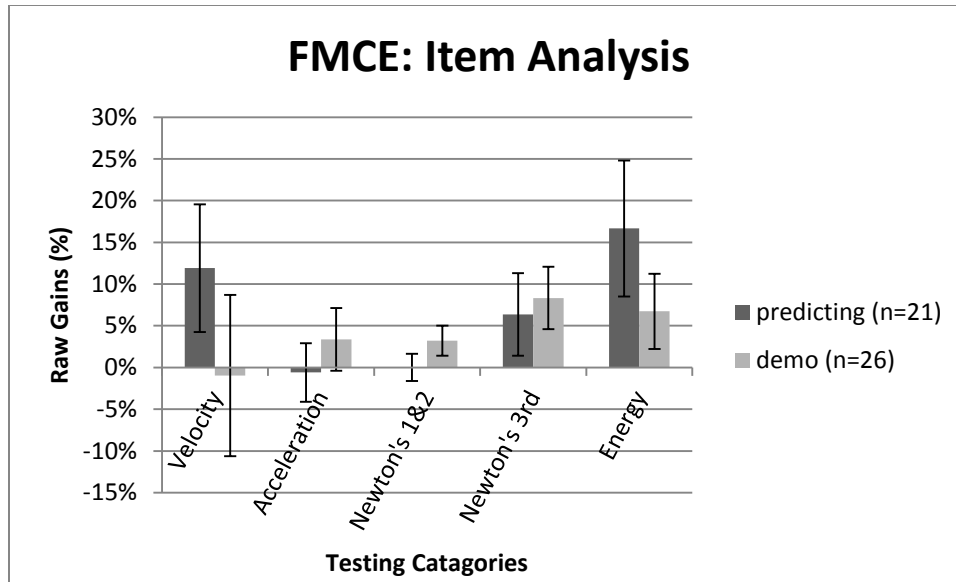


Figure 13: Item analysis for the FMCE. The predicting and demonstration group's raw gains are broken down by the five categories of the test. The sections on Newton's 3rd Law and Energy were not a part of the treatment.

Table 4: Statistical values of the FMCE broken down by category.

Statistical Values		Velocity	Acceleration	Newton's 1 & 2	Newton's 3rd	Energy
Predicting	Mean	12%	-1%	0%	6%	17%
	Standard Deviation	35%	16%	7%	23%	37%
	Count	21	21	21	21	21
	Uncertainty	8%	4%	2%	5%	8%
Demonstration	Mean	-1%	3%	3%	8%	7%
	Standard Deviation	49%	19%	9%	19%	23%
	Count	26	26	26	26	26
	Uncertainty	10%	4%	2%	4%	5%

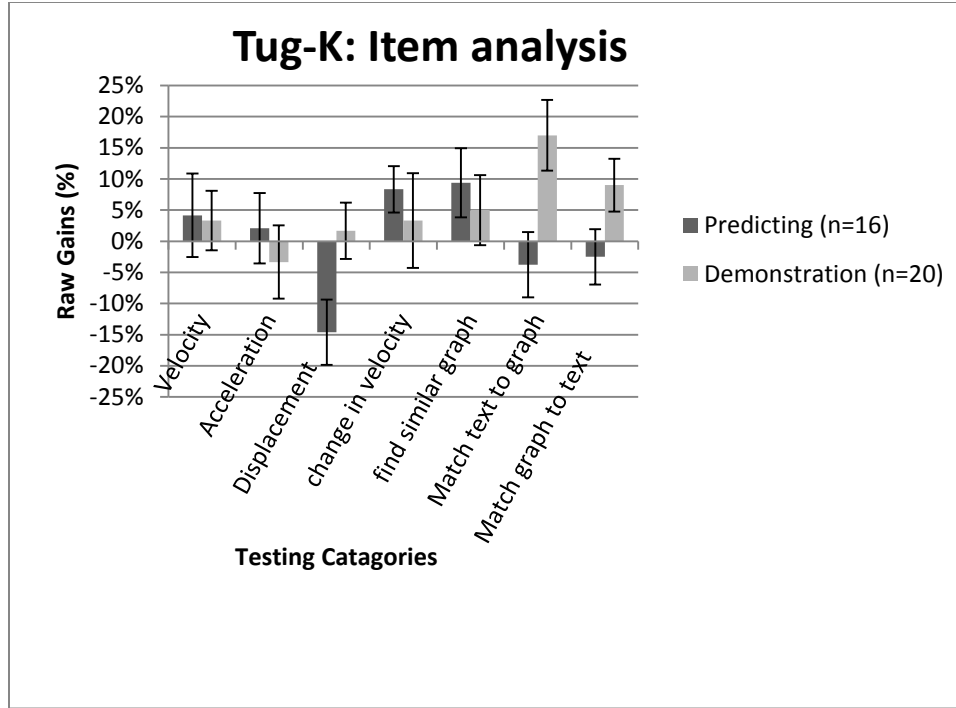


Figure 14: Item analysis for the Tug-K. The predicting and demonstration group's raw gains are broken down by the seven categories of the test.

Table 5: Statistical values for the Tug-K broken down by category.

	Statistical Values	Velocity	Acceleration	Displacement	change in velocity	Find Similar Graph	Match text to graph	Match graph to text
Predicting	Mean	4%	2%	-15%	8%	9%	-4%	-3%
	Standard Deviation	0.27	0.23	0.21	0.15	0.22	0.21	0.18
	Count	16	16	16.0	16.0	16	16	16
	Uncertainty	7%	6%	5%	4%	6%	5%	4%
Demonstration	Mean	3%	-3%	2%	3%	5%	17%	9%
	Standard Deviation	0.21	0.26	0.20	0.34	0.25	0.25	0.19
	Count	20	20	20	20	20	20	20
	Uncertainty	5%	6%	5%	8%	6%	6%	4%

As mentioned above, as part of this study I had students draw what they thought a graph would look like of a person moving away from a point of origin and then coming back to that point of origin. I had the students draw the same motion at the beginning of the year (August), the middle of the semester (October) and the end of the semester (December). The graphs were graded solely on whether or not they resembled a picture of the motion or not. This was designated by any graph that started at some point, moved away from that point and ended back at the starting point. Figure 15 gives the results of those graphs for each group. These graphs point out that the students do have the misconception of drawing motion graphs as a literal picture. They also hold onto this misconception from August through October. Sometime after October these students reconciled this misconception and in December the vast majority of both groups stopped drawing the graph as a literal picture. This is an important step because Maries and Singh found that changes in conceptual understanding are tough when students are still holding on to their misconceptions (2013). If students haven't reconciled their misconception by October, they may not have fully grasped the concepts on motion either. This could be a reason for low FMCE and Tug-K scores as well.

Figure 16 shows one student's series of graphs through the semester. When we look at the mechanics of the graphs, we can see that there is interesting information provided in the first graph besides an axis. This student gives some numbers on the axis and feels the need to explain the lines on the graph. As we progressed to the next graph we begin to see more of a well-defined axis. Each axis is now labeled and the origin is defined. There are also no descriptions drawn in the graph, just a line. In the third representation, again both axis are labeled but now the student has added a negative aspect to the x-axis. The graph here is now looking like the motion of the object in the exercise.

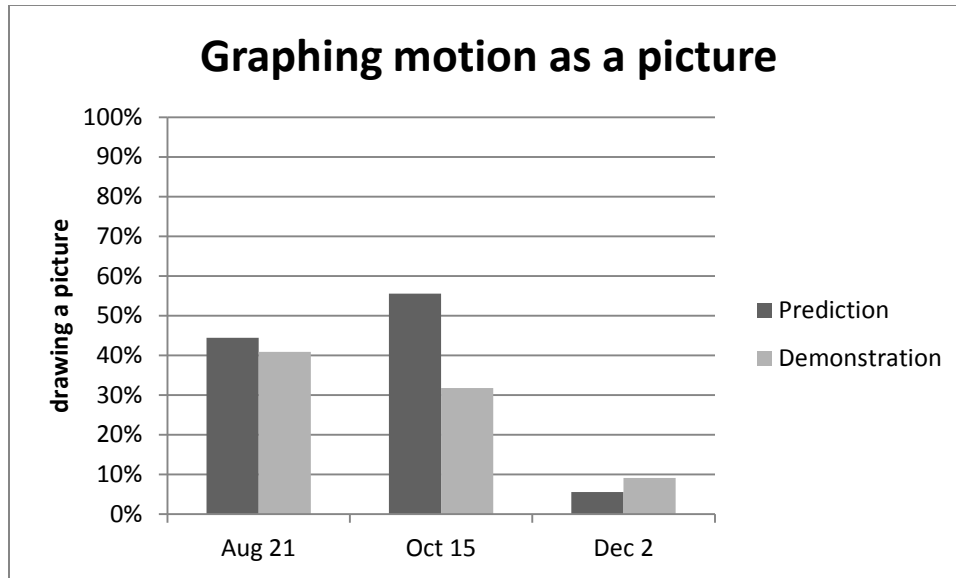


Figure 15: Progress of students drawing motion as a picture over the course of three months: August, October and December.

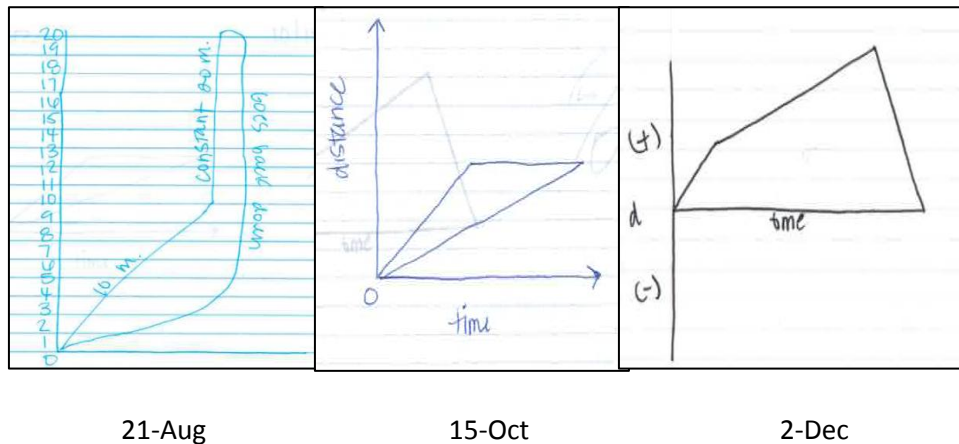


Figure 16: Copy of student work. This shows the progression of one student's work from my motion graphing problem in August, October and December.

Not only can we see a progression of students diminishing misconception of graph as a picture, but we can also see the mechanics improving through the course of the semester. The mechanics of graphing however, does not translate to conceptual understanding. I think it is

evident that even though students became better at graphing and showing the necessary parts of a graph, they still struggled with the concept of presenting a graph that mimics this motion.

In appendix B, I've listed the different motion activities performed during my study. The biggest change occurred toward the end of the activities. This is when I started to have the students work with graphs that involved changes in the direction of motion. Up till this point we had only dealt with one directional motion. When the students had to deal with motion changing directions is when we appear to see the changes in their graphing skills, not drawing the graph as a picture of the motion.

Conclusion

Research has shown that using varying degrees of interactive lecture demonstrations in the classroom can have a significant effect on student achievement. The goal of my study was to try and replicate that effect with a group of students more actively engaged in predicting what a graph of motion was going to look like rather than simply watching a demonstration. From the data analysis, the scores on the FMCE from pretest to posttest do show an average five percent gain for both prediction and demonstration groups. This is quite low when making the comparison to other research involving predictions and demonstrations. I was unable to show any statistical advantage of having a class making predictions about motion over seeing demonstrations. Breaking my data down into gender to see any gender bias or separating the assessment test into categories, was inconclusive. I am unable to support or deny that one group will perform better or worse on the FMCE or Tug-K by the methods I've used.

I believe there are several factors that contributed to not seeing better posttest results. The greatest factor is limiting the seven steps of the ILD process. In their 1990 study, Sokoloff and Thornton place emphasis on learning being enhanced when students can discuss their results with peers. It is also the way scientists actually work (Sokoloff and Thornton, 1990). This is the time when they confront their confusion and resolve that confusion through discussion. Taking this discussion out was the biggest difference in my study and the study done by other researchers. I also believe I greatly underestimated how strong students hold on to their prior misconceptions about a graph looking like a picture of the motion. If students never resolve their graphing misconception they will hold onto it. As noted by Beichner and Saul, when graphical issues are improved, student's conceptual understanding will also increase (Beichner and Saul, 2014). In the future I will spend more time in the beginning of the year going over graphs. I feel

if students had a strong understanding of making and labeling graphs correctly, they could focus more about the graphing concept rather than the mechanics. I didn't spend much time on graphs this year, outside the basics, because I wanted to rely on the prediction and demonstration process to develop their skills. For the types of predictions made, the majority of the motion demonstrated was one directional. We spent most of our time acquiring the understanding of what motion would look like going away or toward a point of origin. Only towards the end did we begin to make prediction on 2-directional motion. If students predicted more graphs that involved motion of different types, they may be forced to think more about what the difference on the graph should look like.

I do believe there were some immeasurable results. In my prediction group, students were upset on the days we didn't do prediction graphs. They enjoyed trying to solve a problem by making sense of prior knowledge. A graph of simple motion didn't involve long equations or plugging in numbers, just them trying to understand a graph. After two weeks into the predictions, students began to get competitive with their peers as to who was going to get the graph correct. I feel this exercise engaged the students and got them involved in the lesson.

I will keep using the motion analysis software. Knowing the limitations from this year's study I will be able to make adjustment for future studies. This will allow a comparison of groups making use of the discussion phase with students who did not.

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Appendix A

Example of a day using video motion analysis (first day):

The Prediction Group: Students were shown a video of a ball rolling across a flat surface. As the ball rolled, it passed by markers in one meter increments for a total of five meters. The students were told the ball was starting at the origin and rolling away from the origin. After the motion stopped the students were asked to draw what they believed a graph of distance vs time would look like. Students were given a few minutes to complete their prediction. Once everyone had something drawn, the video was shown again. This time a graph was shown being drawn in real-time as the ball was rolling. Then students were then asked to label their graph as correct or draw the correct graph. With the real-time graph still showing on the board, I would discuss what the graph is showing. How distance is changing with time. We also had a brief discussion about what a graph would look like if the ball were rolling faster.

The demonstration Group: In this group the students were shown the exact motion as the prediction group. Instead of making any prediction, they were shown the graph being drawn in real-time as a demonstration of what a graph of distance vs time would look like. Students would then draw the graph in a journal. After everyone copied the graph from the board, we also had a discussion about the graph. How distance is changing with time. We also had a brief discussion about what a graph would look like if the ball were rolling faster.

Appendix B
Daily list of the types of motions used in the study:

Date	Type of graph	Direction of motion	Type of velocity
Sep-6	distance vs time	Away from origin	constant
Sep-11	distance vs time	Toward origin	constant
Sep-13	distance vs time	Through origin	constant
Sep-23	velocity vs time	Away from origin	constant
Sep-30	velocity vs time	Toward origin	constant
Oct-8	distance vs time & velocity vs time	Away from origin	constant
Oct-15	acceleration vs time & Force vs time	Away from origin	constant
Oct-15	GRAPH		
Oct-17	distance vs time & velocity vs time	Toward origin	constant
Oct-21	acceleration vs time & Force vs time	Toward origin	constant
Oct-23	distance vs time & velocity vs time	Through origin	constant
Oct-25	acceleration vs time & Force vs time	Away from origin	constant
Oct-29	distance vs time & velocity v time	Away from origin	increasing
Nov-4	acceleration vs time	Away from origin	constant
Nov-7	distance vs time & velocity vs time	Away then toward	constant
Nov-13	acceleration vs time & Force vs time	Away from origin	constant
Nov-15	distance vs time & velocity vs time	Toward then away	decreasing
Nov-19	acceleration vs time & Force vs time	Away from origin	constant
Dec-2	GRAPH		

Appendix C

Student graphing problem:

A man starts running as fast as he can from a starting point. He runs for ten meters then jumps on a skateboard and rolls toward a wall. He then pushes on the wall and rolls back to the starting line.

Appendix D IRB

Application for Exemption from Institutional Oversight

Unless qualified as meeting the specific criteria for exemption from Institutional Review Board (IRB) oversight, ALL LSU research/ projects using living humans as subjects, or samples, or data obtained from humans, directly or indirectly, with or without their consent, must be approved or exempted in advance by the LSU IRB. This Form helps the PI determine if a project may be exempted, and is used to request an exemption.



Institutional Review Board
Dr. Robert Mathews, Chair
131 David Boyd Hall
Baton Rouge, LA 70803
P: 225.578.8692
F: 225.578.5983
irb@lsu.edu
lsu.edu/irb

– Applicant, Please fill out the application in its entirety and include the completed application as well as parts A-F, listed below, when submitting to the IRB. Once the application is completed, please the completed application to the IRB Office or to a member of the Human Subjects Screening Committee. Members of this committee can be found at <http://research.lsu.edu/CompliancePoliciesProcedures/InstitutionalReviewBoard%28IRB%29/item24737.html>

– A Complete Application Includes All of the Following:

(A) A copy of this completed form and a copy of parts B thru F.

(B) A brief project description (adequate to evaluate risks to subjects and to explain your responses to Parts 1&2)

(C) Copies of all instruments to be used.

*If this proposal is part of a grant proposal, include a copy of the proposal and all recruitment material.

(D) The consent form that you will use in the study (see part 3 for more information.)

(E) Certificate of Completion of Human Subjects Protection Training for all personnel involved in the project, including students who are involved with testing or handling data, unless already on file with the IRB. Training link: (<http://phrp.nihtraining.com/users/login.php>)

(F) IRB Security of Data Agreement: (<http://research.lsu.edu/files/item26774.pdf>)

1) Principal Investigator: Charles Redding

Rank: Graduate Student

Dept: Natural Science

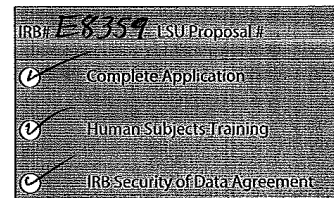
Ph: 225-933-0933

E-mail: credd321@cox.net

2) Co Investigator(s): please include department, rank, phone and e-mail for each

*If student, please identify and name supervising professor in this space

Dr. Dana A. Browne, Professor, Dept. of Physics and Astronomy, 578-6843, phowne@lsu.edu



3) Project Title:

Will Interactive-Engagement, through the use of motion analysis technology, have the same effect if used in a passive role compared t an active role

Study Exempted By:
Dr. Robert C. Mathews, Chairman
Institutional Review Board
Louisiana State University
203 B-1 David Boyd Hall
225-578-8692 | www.lsu.edu/irb
Exemption Expires: 7/29/2016

4) Proposal? (yes or no) NO

If Yes, LSU Proposal Number

Also, if YES, either

☐ This application completely matches the scope of work in the grant

OR

☐ More IRB Applications will be filed later

5) Subject pool (e.g. Psychology students)

All physics students at Livonia High School

*Circle any "vulnerable populations" to be used: (children <18; the mentally impaired, pregnant women, the ages, other). Projects with incarcerated persons cannot be exempted.

6) PI Signature

Charles Redding

Date

7/8/2013

(no per signatures)

** I certify my responses are accurate and complete. If the project scope or design is later changes, I will resubmit for review. I will obtain written approval from the Authorized Representative of all non-LSU institutions in which the study is conducted. I also understand that it is my responsibility to maintain copies of all consent forms at LSU for three years after completion of the study. If I leave LSU before that time the consent forms should be preserved in the Departmental Office.

Screening Committee Action:	Exempted <input checked="" type="checkbox"/>	Not Exempted <input type="checkbox"/>	Category/Paragraph	1
Signed Consent Waived?:	Yes <input type="checkbox"/>	No <input checked="" type="checkbox"/>		
Reviewer	Mathews	Signature	<i>Robert Mathews</i>	Date
				7/30/13

VITA

Charles W. Redding was born in Jackson, Mississippi, in March 1973. He attended elementary, middle, and high school in Jackson, Mississippi. He graduated from Jackson Prep in May of 1991. The following August He entered University of Mississippi and in August 1996 earned a Bachelor's Degree in Biology. In 1997 he entered Belhaven College and earned a Bachelor's Degree in Chemistry in 1999. He entered the Graduate School at Louisiana State University Agricultural and Mechanical College in June 2012 and is a candidate for a Master of Natural Sciences. He is currently a high school Physics and Chemistry teacher at Livonia High School in Pointe Coupee Parish.