Introducing Non-Calculus Ready First Year Engineering Students to Metacognition Skills to Improve Academic Performance

Anika C. Pirkey[a], Jake Follmer[b], David J. Klinke II[a], D. J, and Lizzie Y. Santiago[c]

a. Department of Chemical and Biomedical Engineering

b. School of Education, College of Applied Human Sciences

c. Fundamentals of Engineering Program

West Virginia University

RUNNING HEAD: PIRKEY, FOLLMER, KLINKE, AND SANTIAGO

Correspondence should be addressed to:

Lizzie Y. Santiago

lizzie.santiago@mail.wvu.edu

Phone: (304) 293-0998

Fundamentals of Engineering Program

West Virginia University

P.O. Box 6101

Morgantown, WV 26506-6102

ABSTRACT

Background

College readiness is declining, increasing the number of students entering college with low math proficiency. These students are historically unable to make progress towards learning engineering skills until they've completed remedial math coursework and have low retention and graduation rates.

Purpose

This work describes a pilot study for a trigonometry based first-year engineering course designed to improve students' performance in trigonometry while targeting the improvement of metacognition skills with the goal of increasing student success and retention.

Design/Method

Twenty-one (21) students were enrolled in the course, which implements a lecture series on metacognition skills and lectures designed to apply trigonometry to real-world engineering problems. One-semester and cumulative GPA and trigonometry and chemistry course grades were compared between the intervention and control groups. The intervention group took the Metacognitive Awareness Inventory (MAI) before and after the intervention along with three exams with embedded metacognitive monitoring questions throughout the course. All statistical analysis was completed in R using appropriate Bayesian statistical methods.

Results

Students in the intervention received an A in their trigonometry courses at a higher rate than the control group. No significant change was seen in one-semester or cumulative GPA or chemistry performance. Improvements in metacognition skills were dependent on content difficulty and student preparation for the exams given.

Conclusion

The importance of developing coursework for non-calculus ready students will continue to increase. While not all results are statistically significant, additional work is warranted with a higher sample size to further examine the non-significant benefits seen in this study.

KEYWORDS: Metacognition, Non-calculus ready, Course Intervention

INTRODUCTION

College readiness is on the decline across the United States, with only 22% of students taking the ACT considered college ready in 2022. ACT and SAT average scores have both decreased in recent years, with average ACT scores dropping from 20.8 to 19.8 and SAT scores dropping from 1068 to 1050 between 2018 and 2022 (ACT Inc., 2022; College Board, 2018, 2022). With this decline in college readiness, more students are entering college with a math proficiency below the level of Calculus 1. Because most core engineering coursework relies on a math proficiency of Calculus 1 or higher, students are often left behind until they can progress far enough in the math curriculum to begin engineering courses. This has the potential to turn away students who are interested in engineering, forcing them to choose other degree programs where they can immediately begin core courses. In addition, retention and graduation rates of students who begin an engineering with low math proficiency are significantly lower than their calculus-ready peers (Jones et al., 2021; Pirkey et al., 2024). With engineering enrollment on the decline since as early as 2016 and a demographic cliff arriving in 2025 that is likely to exacerbate the enrollment problem, it is imperative that engineering programs find ways to improve enrollment and retention in their programs (American Society for Engineering Education, 2021; Schuette, 2023).

One approach to improving the outcomes of students is through the development of transferable learning skills such as metacognition skills. Metacognition is defined as the knowledge and regulation of one's own thought processes and encompasses metacognitive knowledge and experiences, goals, strategies, and the collaborations among these areas (Brown, 1977; Cunningham et al., 2015; Flavell, 1979). The successful application and regulation of these areas assists in metacognitive monitoring and is necessary to promote successful strategic learning (Dinsmore & Parkinson, 2013).

Metacognitive monitoring is defined as a student's real-time analysis and awareness of their performance while completing a task and has been linked to academic success in problem-solving, learning, and performance (Nietfeld et al., 2006; Stanton et al., 2021). A small, but growing body of literature shows courses have been developed across engineering disciplines and indicates that metacognitive monitoring may be important in engineering problem solving (Case et al., 2001; Cunningham et al., 2015; S. Goldberg et al., 2016; S. R. Goldberg et al., 2015; L. Santiago et al., 2024). Creating coursework to fill the gap in engineering education for low math proficiency students while targeting transferable metacognition skills could prove beneficial in improving student success.

The goal of this study was to develop and implement an intervention course for students enrolled in an engineering program with a Trigonometry level math proficiency. The course runs in parallel with students' Trigonometry course and reinforces the skills taught by the math course. These skills are then applied directly to engineering examples to connect the concepts to real-world applications. In addition to the trigonometry course work, a three-lecture series on metacognition and self-regulated learning was implemented with the goal of making students aware and improving the use of these skills. It is expected that the course will improve students' metacognition and self-regulated learning skills along with their math course performance.

LITERATURE REVIEW

Non-Calculus Ready First Year Engineering Students. Engineering programs have historically had very low retention rates, with only 50 – 60% of students who begin university as an engineering major graduating with an engineering degree within six years (American Society for Engineering Education, 2017; Geisinger & Raman, 2013). These graduation rates drop considerably, to between 20% and 45%, when considering students who do not start their engineering curriculum at a Calculus 1 or higher math proficiency (Jones et al., 2021; Van Dyken et al., 2015; Van Dyken & Benson, 2019).

Middleton et al. reported that if an engineering student's first math course was pre-calculus or lower, they were less than half as likely to persist past their second year in engineering when compared with their peers who took Calculus 1 or higher, with nearly three quarters of students leaving their engineering program within 5 years (Middleton et al., 2014). Our institution reports only 50% retention of non-calculus ready students in engineering after two years without intervention (Pirkey et al., 2024; Pirkey & Santiago, 2021). While some institutions have created coursework geared towards improving the retention of non-calculus ready engineering students, many are unprepared to work with this population (Monte & Hein, 2003; Standridge et al., 2003). As the proportion of non-calculus ready students continues to increase due to the decrease in college readiness and math proficiency across the country, it will become imperative that institutions implement new courses or changes to their curriculums to serve this population (ACT Inc., 2022; College Board, 2022)

Self-Regulated Learning and Metacognition. Self-regulated learning is defined as "an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment" (Pintrich, 2005). Many models of self-regulation, such as the one described by Zimmerman, include four phases: goal setting, monitoring, control, and reaction and reflection (Pintrich, 2005; Zimmerman, 2000). These four phases can then be applied to four areas for regulation: cognition, motivation, behavior, and context and align with various skills and strategies that can aid in the development of self-regulation. The monitoring of cognition and subsequent regulation of one's own thought processes is known as metacognition and is one of the three elements along with motivation and behavior that define self-regulated learning (Zimmerman, 2008).

Metacognition, and more specifically metacognitive monitoring, occurs through metacognitive knowledge, metacognitive experiences, goals or tasks, and actions or strategies. Metacognitive knowledge refers to the subset of knowledge a person has about the world, other people's diverse tasks, goals, actions, and experiences, and how they fit into the world. An example of this is a student's held belief that they are not as good at math or science as their classmates. Metacognitive experiences are the cognitive and affective experiences one has during intellectual activities such as the feeling of not understanding a lecture that was given. Finally, goals and tasks refer to the objectives of learning while the actions or strategies refer to the behaviors used to achieve those goals. These four phenomena work both independently and collaboratively, and learners must effectively regulate the relationships between them to promote strategic learning (Flavell, 1979).

This study focuses on metacognitive knowledge, which is linked to improved academic performance by improving students' abilities to identify appropriate learning strategies, transfer knowledge acquired in one setting or situation to another, and identify their own academic strengths and weaknesses and adapt accordingly (Pintrich, 2002).In addition, metacognition plays an important part in problem solving, a key skillset within engineering (Cunningham et al., 2015; Jonassen, 2010; Pintrich, 2002). Unfortunately, while a small body of work exists exploring the role of metacognition in engineering education, much of the research has been done in controlled experimental settings as opposed to inside the classroom and focuses on more generally applicable skills such as reading and oral communication (Case et al., 2001; Cunningham et al., 2015; Flavell, 1979; Gafoor. K & Kurukkan, 2016; S. Goldberg et al., 2016; S. R. Goldberg et al., 2015; Jonassen, 2010; L. Santiago et al., 2024).

THEORETICAL FRAMEWORK

Flavell's classic paper on metacognition breaks down metacognitive knowledge into three primary categories: strategy (strategic knowledge), task (knowledge of cognitive tasks), and person (self-knowledge) (Flavell, 1979). These three factors are common features in many different metacognition frameworks and interact with and affect one another to shape the outcome of learning (Cunningham et al., 2015; Pintrich, 2002).

Strategic knowledge encompasses all of the tools and general strategies needed for students to learn. These strategies are typically general so that they can be applied to a wide variety of problems (Cunningham et al., 2015; Flavell, 1979). In addition to having knowledge of the various strategies that may be effective in solving a problem, learners also require knowledge of various cognitive strategies that may be useful in planning, monitoring, and regulating their learning (Pintrich, 2002). Knowledge of these strategies is intertwined with a learner's knowledge of cognitive tasks.

Knowledge of cognitive tasks first includes the ability to discern the level of difficulty of a task. This difficulty may be a result of the amount and quality of available information, the complexity of problems, or the cognitive load required to complete a task, such as the difference between remembering the main idea of a story and remembering the story word for word (Cunningham et al., 2015; Flavell, 1979; Pintrich, 2002). In addition to understanding the difficulty of the problem, knowledge of cognitive tasks also includes a knowledge of which learning and cognitive strategies are most appropriate for different learning tasks. This can be impacted not only by the task itself, but also by the situational variables affecting the task such as the social, cultural, and environmental concerns (Pintrich, 2002).

Finally, self-knowledge encompasses the beliefs and understandings one has about their own learning. First, learners' held beliefs of the importance of a task as well as their belief in their ability to solve a problem impact their motivation to do so. Self-knowledge can also be directly related to strategic knowledge; a learner may recognize that their strengths or weaknesses lie in certain tasks or styles of learning and be able to adjust to play to their strengths. One may also recognize their tendency to over rely on certain strategies that may not be the most effective for a certain problem. A key element of self-knowledge is the ability to recognize the depth and breadth or their own knowledge, or when one does or does not understand or know something (Pintrich, 2002). This element is key to a learner's ability to accurately self-assess and correct their cognitive processes.

This study focuses on students' calibration, which is a subsection of self-knowledge defined as the difference between students' confidence in their own abilities and their actual performance on academic tasks. Throughout the learning process, students are required to make two key judgements. First, during the studying process, students must adequately gauge whether or not they have learned the material they are studying. Second, as students answer questions, they must be able to ascertain whether or not they have successfully answered the questions during the exam. These two self-reflections are known as a judgement of learning and a confidence judgement, and the accuracy of both is critical to the guidance and success of students' self-regulated learning practices (Dinsmore & Parkinson, 2013; Labuhn et al., 2010).

METHODOLOGY

Participants. Twenty-one (21) first-year engineering students enrolled in their second semester participated in the study. All students were enrolled in Trigonometry at the time of the study and were a part of a first-year engineering program at a Land Grant Institution in the Mid-Atlantic Region in Spring 2023.

Participant demographics and high school academic performance data are summarized in Table 1. A matched control group of 38 students enrolled in trigonometry, but not enrolled in the intervention course was created using gender, high school GPA, and Math SAT scores as covariates. The control and experimental groups were not statistically different (Figure S1, Proportion of male students average difference = 1.66%, 95% HDI = [-15.7% - 16.4%], 59.6% probability of a difference > 0, hGPA average difference = -0.03 GPA points, 95% Highest Density Interval (95%HDI) = [-0.19 -0.14 GPA points], 62.2% probability of a difference < 0 ; Math SAT average difference = 1.21 points, 95%HDI = [-16.3-18.6], 44.6% probability of a difference < 0, Math ACT average difference = 0.653 points, 95%HDI = [-2.43 - 3.74 points], 32.2% probability of a difference < 0).

First Year Engineering Program. Upon acceptance to the engineering school, students who are not bringing in college credit or AP Exam credit for math courses must take a placement test to determine which level of math they should be placed into. To move from the first-year program into their chosen department at the time of the study, students must maintain a cumulative GPA (cGPA) of at least 2.25 and complete a set of six core courses ((Fundamentals of Chemistry 1, Calculus 1, Introduction to Composition and Rhetoric, First Year Seminar, Engineering Problem Solving 1, and Engineering Problem Solving 2) with a grade of C or better. Students who place into College Algebra when they begin college must complete the course along with Trigonometry before they are able to advance to Calculus 1 and Engineering Problem Solving 1 cannot be completed until students advance to either the full semester version of Calculus 1 or the second half of the two-semester version of the course. To earn an engineering degree, students in Computer Science must complete 3 semesters of college calculus while those in any other engineering discipline must complete four semesters.

Course Description. This course was designed as a supplemental course to improve student's trigonometry skills. The overall structure of the course is based on a similar study conducted in education students by Cogliano et. al. (Cogliano et al., 2021). An approximate course schedule detailing the topics covered is provided in Table 2. The order of topics was chosen based on the order of topics taught by the math department at the time of the study and the timing was such that each topic was typically covered one week after the students initially were introduced to the concepts in their trigonometry class. Each basic trigonometry topic was covered through a "Skills" lecture and an "Applications" lecture. In Skills Lectures, the basic concepts of the topic are reinforced through lecture and basic examples of the skills. These lectures typically mirrored what was taught in the trigonometry class in order to give students a second exposure to the basics of the concepts before applying them to more complex problems. Applications Lectures were taught exclusively through real-world example problems. This often included complex word problems pulled from different engineering disciplines, hands on demonstrations, or lab activities with accompanying calculations. The goal of the Applications Lectures was to provide more challenging problems than were typically provided in the trigonometry classroom while also providing real-world applications of different trigonometric skills to reinforce the importance of their mastery for success in engineering.

In addition to the mathematics component of the course, a three-lecture series with accompanying in class activities and homework was delivered early in the semester (weeks 3-5) to introduce students to key concepts related to retrieval practice, self-regulation, and metacognition. Throughout the semester, students were asked to refer to these skills by answering short reflections on their performance on homework, quizzes, and exams.

Metrics Used. Demographic and high school performance data including gender, high school GPA, and Math SAT and ACT scores was collected at the start of the study. Institutional data including students' cumulative GPA, one semester GPA, and trigonometry and chemistry grades were collected at the end of the semester when the study concluded (Spring 2023). All data was collected for both the control and experimental groups.

The Metacognitive Awareness Inventory (MAI) was given to the experimental group during the first and last weeks of the semester to measure pre and post metacognitive awareness The MAI is a self-report instrument used to measure metacognitive awareness under the broad categories of knowledge of cognition and regulation of cognition (Schraw & Dennison, 1994). The assessment asks students to rank 52 statements on a scale from 0 to 100 based on how well they believe the statement applies to them.

In addition to the MAI, students in the experimental group were given three exams over the course of the semester with built in questions to gauge their calibration as it related to their ability to solve problems. Prior to solving each question, students were asked "How confident are you in your ability to accurately complete problems like this one?" and requested to provide a rating between 0 and 100. At the end of each question, students were asked "How confident are you in the solution you've provided to this problem?" and again asked to provide a rating between 0 and 100. The Midterm Exam was used as a Metacognition Pre-Test to gauge student's performance bias shortly after being introduced to the metacognition concepts. The Metacognition Post-Test used questions that were nearly identical to those presented on the Pre-

Test where the numbers and math procedure stayed the same, but the story presented in the word problem was different. The Final Exam also had performance bias questions, but the content was related to course material from midterm onwards and contained different questions from the Metacognition Pre- and Post- Tests. Each time students were asked to rate their confidence, this rating was compared to their actual performance on the question being rated by subtracting their actual performance from their confidence to obtain a rating of bias, which was negative if students were underconfident and positive if students were overconfident. The absolute value of the bias calculation was considered the students' absolute accuracy. Absolute accuracy is compared between the pre and post tests and the mean difference between the pre and post accuracy scores is presented.

Statistical Analysis. All statistical analysis was performed in R v4.3.1. The matched random control group was created using the MatchIt package (v4.5.5) and accounted for gender, high school GPA, and Math SAT scores as covariates (Ho et al., 2011). The BEST package (v0.5.4) was used to estimate the mean value of the parameter measured within the experimental group or the size of the effect the intervention course had on student performance parameters such as mean cumulative GPA compared to the control group (Kruschke, 2013). The package uses minimally informative priors including normal priors with large standard deviations for the mean, broad uniform priors for standard deviation, and a shifted-exponential prior for the normality parameter and equal variance is assumed between treatment groups (Kruschke, 2013; Meredith & Kruschke, 2021). Data is reported as a 95% Highest Density Interval (HDI) along with a mean of the credible values for the difference between groups (average difference) and a probability that the parameter is less than 0.

Comparison of proportions between groups was done via methods described by Andrew Heiss using the brms package (v2.19.0) in R (Heiss, 2023). Data is reported as the mean credible value of the difference between proportions as well as 95% HDI and the probability that the difference in proportions is less than 0. In all tests, a probability of 5% or less (or 95% or more in the case of bias values less than 0) was considered statistically significant. All R code and deidentified data is available at https://github.com/arcoolbaugh/ENGR_Metacognition.

Study Approval. This study was approved by the West Virginia University Institutional Review Board (WVU-IRB, Protocol # 2212697700).

RESULTS

Difference in Metacognition Skills from the Intervention. Of 21 participants in the intervention, 17 had MAI scores for both the pre and post-tests. Scores were totaled out of 5200 (100 points per question). The average pre-MAI score was 3686, while the average post-MAI score was 3739 (Figure 1, average difference = 51.3 points, 95% HDI = [-217 – 316 points], 34.5% probability of a difference < 0). This difference was not statistically significant. It was noted that 9 of 17 students' scores decreased between the pre and post-MAI, indicating a decrease in metacognitive awareness.

To compare changes in performance calibration, students' absolute accuracy in their confidence rating compared to their actual performance on scales of 0 – 100 were compared between the Metacognition Pre-Test (Midterm Exam) and the Metacognition Post-Test. The Pre- and Post-Test examined identical content and each contained one easier content question and one more difficult content question. The average change in absolute accuracy between the pre and post-test on the easy content question was -3.87 points before completing the question and -2.72 points after completing the question, indicating minimal change in calibration (Figure 2, left column, average pre-question difference = -3.87 points, 95% HDI = [-14.3 – 6.12 points], 78.0% probability of a difference < 0; average post-question difference = -2.72points, 95% HDI = [-9.86 – 4.56 points] 78% probability of a difference < 0).

In contrast, the average change in absolute accuracy between the pre and post-test on the difficult content question was 19 points before completing the question and 13.9 points after completing the question, indicating a significant decrease in calibration between the pre and post-test (Figure 2, right column, average pre-question difference = 19.6 points, 95% HDI = [10.5 – 28.6 points], 0.0% probability of a difference < 0; average post-question difference = 14.2 points, 95% HDI = [5.8 – 22.3 points] 0.1% probability of a difference < 0). The significant difference in calibration between the easy and difficult content questions indicates that content difficulty plays a role in students' ability to accurately gauge their own performance.

It was noted that students did not study to prepare for the Metacognition Post-Test in the same way they prepared for the Pre-Test. This was because the pre-test was also the Midterm Exam and was a heavily weighted assignment in the course while the Post-Test was treated as low weight completion grade. To assess whether students' feeling of preparedness impacted their calibration, the same comparison of calibration was done between the Metacognition Pre-Test (Midterm Exam) and the Final Exam for the course. These exams covered different content but were structured similarly with an easier content question and a more difficult content question. In addition, students were more likely to put in similar effort in preparation for the two exams because they were both heavily weighted grades in the course.

The average change in absolute accuracy between the pre-test and the final exam on the easy content question was -7.92 points before completing the question and -7.3 points after completing the question, indicating a significant improvement in calibration when student preparedness is taken into account (Figure 3, left column, average pre-question difference = -7.92 points, 95% HDI = [-15.3 – -0.60 points], 98.3% probability of a difference < 0; average post-question difference = -7.30 points, 95% HDI = [-12.8 – 1.77 points] 99.4% probability of a difference < 0).

The average change in absolute accuracy between the pre-test and the final exam on the difficult content question was 0.58 points before completing the question and 2.39 points after completing the question, indicating no significant change in calibration (Figure 3, right column, average pre-question difference = 0.583 points, 95% HDI = [-10.6 – 11.6 points], 45.7% probability of a difference < 0; average post-question difference = 2.39 points, 95% HDI = [-8.51 – 13.2 points] 32.7% probability of a difference < 0). While students still struggle significantly with performance calibration on more difficult content, much of the effect is mitigated when student preparedness is taken into account, leading to a lack of change in calibration rather than a significant decrease in calibration as was seen when comparing the pre-test, which students prepared for, and the post-test, which most students did not prepare for.

Difference in Academic Performance. Throughout the course of the study, all students in the control and experimental groups were enrolled in Trigonometry. Figure 4A shows the percentages of each group that received a certain grade in their Trigonometry course. In the control group, 33/38 students (86.8%) passed their math course with an A, B, or C while 20/21 (95.2%) of the experimental group passed (Figure S2A, average difference = 6.26%, 95% HDI = [-12.3% - 22.5%], 21.5% probability of a difference < 0). With a 21.5% probability that the difference is less than 0, this difference is likely not significant. There was, however, a statistically significant difference in the number of students who were able to obtain an A in their trigonometry course in each group. Only 5/38 (13.2%) of the control group received an A in trigonometry while 8/21 (38.1%) of the experimental group received an A (Figure S2C, average difference = 23.6%, 95% HDI = [0.11% - 48.1%], 2.45% probability of a difference < 0). Students with below calculus-level math proficiency in the studied engineering program often show additional struggles in their chemistry courses. As a result, we wanted to investigate whether or not the intervention had an effect on students' chemistry grades (Figure 4B). In the control group, 23 of the 31 students enrolled in a chemistry course (74.2%) passed with an A, B, or C while 17 of 20 (85.0%) of the experimental group passed (Figure S2B, average difference = 8.95%, 95% HDI = [-14.6% - 31.9%], 22.1% probability of a difference < 0). When reviewing the number of students to obtain an A in chemistry, 4/31 students in the control group (12.9%) and 4/20 in the experimental group (20%) were able to obtain an A (Figure S2D, average difference = 7.15%, 95% HDI = [-14.3% - 30.5%], 26.2% probability of a difference < 0). These results were not considered significant.

Difference in GPA Between Groups. Figure 5 shows the average cumulative GPA (cGPA) and one-semester GPA for students in the control and experimental groups. The average cGPA in the control group at the completion of the study was 3.11 ±0.60 while the experimental group had an average cGPA of 3.18 ±0.54 (Figure 5, left column, average difference = 0.06 GPA points, 95% HDI = [-0.26 – 0.39 GPA points], 35.4% probability of a difference < 0). The average one-semester GPA in the control group at the completion of the study was 2.91 ±0.71 while the experimental group had an average cGPA of 3.04 ±0.69 (Figure 5, right column, average difference = 0.12 GPA points, 95% HDI = [-0.28 – 0.52 GPA points], 27.0% probability of a difference < 0). While more impact was seen on the one-semester GPA when compared to cGPA, these results are not likely to be significant.

DISCUSSION

The importance of self-regulated learning and strong metacognitive knowledge for learning has been shown repeatedly across multiple domains of education research and continued work in this field is warranted to improve students' performance in engineering problem solving (Case et al., 2001; Cunningham et al., 2015; Flavell, 1979; Gafoor. K & Kurukkan, 2016; S. Goldberg et al., 2016; Jonassen, 2010; Nietfeld et al., 2006; Pintrich, 2002, 2005; L. Santiago et al., 2024; Stanton et al., 2021; Zimmerman, 2000, 2008; Zimmerman & Kitsantas, 1997). Based on this study, non-calculus ready students' knowledge of the difficulty of a task, self-knowledge of their abilities to solve problems, and thus their ability to accurately predict their performance and modify their cognitive practices, is poor, particularly on difficult content questions. While many of the effects of the intervention were not statistically significant, influencing student's beliefs of the importance of the tasks by making the metacognition assignments "higher stakes" would likely have an influence on their preparation for the metacognition exams and their willingness and perceived ability to accurately complete the assignments. Based on the results showing the impact of preparation on metacognitive monitoring during exams, this would likely have a significant impact on the results. In addition, because this was a pilot study with relatively low participation, it is worth pursuing the continuation of this work in order to increase the number of students in the intervention group, which may push some of the smaller but positive results in this study towards statistical significance.

Finally, while this course is currently being evaluated as a stand-alone intervention, the possibility exists to combine it with a previously discussed college-algebra based intervention focused on promoting critical thinking and engineering problem solving skills to create a two-semester series that could provide additional benefit to students (L. Y. Santiago et al., 2016, 2017). Our prior work shows that while a one-semester intervention is helpful in improving math progression and engineering persistence in early semesters, the benefits diminish over time as students begin struggling in higher level mathematics coursework (Pirkey et al., 2024). Providing and encouraging students to participate in a multi-semester set of coursework to support them through their initial mathematics courses while developing these transferable learning skills may work to improve the long-term effectiveness of both interventions.

ACKNOWLEDGEMENTS:

This work was supported by grants received by Lizzie Y. Santiago from the National Science Foundation (Project # 10030318, Grant # DUE-2236126). The content is solely the responsibility of the authors and does not necessarily represent the official views of the NSF.

AUTHOR BIOGRAPHIES:

Anika C. Pirkey is a PhD Candidate and Teaching Assistant Professor in the Department of Chemical and Biomedical Engineering at West Virginia University, P.O. Box 6102, Morgantown, WV, USA, 26506; anika.pirkey@mail.wvu.edu

D. Jake Follmer, Ph.D. is an Assistant Professor in the School of Education in the College of Applied Human Sciences at West Virginia University, 375 Birch Street, P.O. Box 6115, Morgantown, WV, USA, 26506; djf00001@mail.wvu.edu

David J. Klinke II, Ph.D. is a Professor in the Department of Chemical and Biomedical Engineering and an Adjunct Associate Professor in the Department of Microbiology, Immunology, and Cell Biology at West Virginia University, P.O. Box 6102, Morgantown, WV, USA, 26506; David.klinke@mail.wvu.edu

Lizzie Y. Santiago, Ph.D. is a Teaching Professor and the Director of the Fundamentals of Engineering Program at West Virginia University, P.O. Box 6101, Morgantown, WV, USA, 26506; lizzie.santiago@mail.wvu.edu

BIBLIOGRAPHY:

ACT Inc. (2022). *The ACT Profile Report - National Graduating Class of 2022*.

American Society for Engineering Education. (2017). *Engineering by the Numbers: ASEE Retention and Time-to-Graduation Benchmarks for Undergraduate Engineering Schools, Departments and Programs*.

American Society for Engineering Education. (2021). *ASEE 2020 Edition Engineering & Engineering Technology By the Numbers*. www.asee.org

Brown, A. L. (1977). *Knowing When, Where, and How to Remember: A Problem of Metacognition*.

Case, J., Gunstone, R., & Lewis, A. (2001). Students' Metacognitive Development in an Innovative Second Year Chemical Engineering Course. In *Research in Science Education* (Vol. 31).

Cogliano, M., Bernacki, M. L., & Kardash, C. M. (2021). A Metacognitive Retrieval Practice Intervention to Improve Undergraduates' Monitoring and Control Processes and Use of Performance Feedback for Classroom Learning. *Journal of Educational Psychology*, *113*(7), 1421–1440. https://doi.org/10.1037/edu0000624

College Board. (2018). *2018 Total Group SAT Suite of Assessments Annual Report*.

College Board. (2022). *2022 Total Group SAT Suite of Assessments Annual Report*. www.collegeboard.org.

Cunningham, P., Matusovich, H. M., Hunter, A. N., & McCord, R. E. (2015). Teaching Metacognition: Helping Engineering Students Take Ownership of Their Own Learning. *Frontiers in Education Conference*.

Dinsmore, D. L., & Parkinson, M. M. (2013). What are confidence judgments made of? Students' explanations for their confidence ratings and what that means for calibration. *Learning and Instruction*, *24*(1), 4–14. https://doi.org/10.1016/j.learninstruc.2012.06.001

Flavell, J. H. (1979). Metacognition and Cognitive Monitoring A New Area of Cognitive-Developmental Inquiry. *American Psychologist*, *34*(10), 906–911.

Gafoor. K, A., & Kurukkan, A. (2016). Self-Regulated Learning: A Motivational Approach for Learning Mathematics. *International Journal of Education and Psychological Research (IJEPR)*, *5*(3).

Geisinger, B. N., & Raman, D. R. (2013). Why They Leave: Understanding Student Attrition from Engineering Majors Why They Leave: Understanding Student Attrition from Engineering Majors. *International Journal of Engineering Education*, *29*(4), 914–925. http://lib.dr.iastate.edu/abe_eng_pubs

Goldberg, S. R., Rich, J. A., & Masnick, A. M. (2015). Efficacy of a metacognitive writing-to-learn exercise in improving student understanding and performance in an engineering Statics course. *American Society for Engineering Education Annual Conference and Exposition*.

Goldberg, S., Rich, J., Masnick, A., Lutz, B., Groen, C., Paretti, M., & Mcnair, L. (2016). Writing-to-learn exercises to improve student understanding and metacognition in an engineering statics course. *2016 ASEE Mid-Atlantic Section Conference*.

Heiss, A. (2023, May 15). *A guide to Bayesian proportion tests with R and {brms}*. Andrewheiss.Com.

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2011). MatchIt: Nonparametric Preprocessing for Parametric Causal Inference. *Journal of Statistical Software*, *42*(8). http://www.jstatsoft.org/

Jonassen, D. H. (2010). Metacognitive Regulation of Problem Solving. In *Learning to Solve Problems: A Handbook for Designing Problem-Solving Learning Environments* (pp. 340–350). Taylor & Francis Group. http://ebookcentral.proquest.com/lib/wvu/detail.action?docID=574578.

Jones, S. A., Cairncross, C., Vandergrift, T., & Kalnin, J. (2021). Persistence of Students who Begin Engineering Programs in Precalculus. *Advances in Engineering Education*, *9*(4).

Kruschke, J. K. (2013). Bayesian estimation supersedes the t test. *Journal of Experimental Psychology: General*, *142*(2), 573–603. https://doi.org/10.1037/a0029146

Labuhn, A. S., Zimmerman, B. J., & Hasselhorn, M. (2010). Enhancing students' self-regulation and mathematics performance: The influence of feedback and self-evaluative standards. *Metacognition and Learning*, *5*(2), 173–194. https://doi.org/10.1007/s11409-010-9056-2

Meredith, M., & Kruschke, J. (2021). *Bayesian Estimation Supersedes the t-Test*. http://sourceforge.

Middleton, J. A., Krause, S., Maass, S., Beeley, K., Collofello, J., & Culbertson, R. (2014). Early Course and Grade Predictors in Undergraduate Engineering Majors. *2014 IEEE Frontiers in Education Conference (FIE) Proceedings*, 1–7. https://doi.org/10.1109/FIE.2014.7044367

Monte, A. E., & Hein, G. L. (2003). Using Engineering Courses to Improve Pre-Calculus Students' Success Background-First Year Engineering at MTU. *Proceedings of the 2003 American Society for Engineering Educations Annual Conference & Exposition*.

Nietfeld, J. L., Cao, L., & Osborne, J. W. (2006). The effect of distributed monitoring exercises and feedback on performance, monitoring accuracy, and self-efficacy. *Metacognition and Learning*, *1*(2), 159–179. https://doi.org/10.1007/s10409-006-9595-6

Pintrich, P. R. (2002). The Role of Metacognitive Knowledge in Learning, Teaching, and Assessing. *Theory Into Practice*, *41*(4), 219–225.

Pintrich, P. R. (2005). The Role of Goal Orientation in Self-Regulated Learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of Self-Regulation* (pp. 451–502). Academic Press. https://www.ebsco.com/terms-of-use

Pirkey, A. C., Morris, M., Klinke II, D. J., Follmer, D. J., & Santiago, L. Y. (2024). *Development of an Engineering Reasoning Course to Improve the Persistence of Non-Calculus Ready First Year Engineering Students*. https://doi.org/https://doi.org/10.31224/3653

Pirkey, A. C., & Santiago, L. Y. (2021, June). Understanding the Educational Path of Non-Calculus-Ready Students in Engineering. *2021 ASEE Virtual Annual Conference Content Access*.

Santiago, L., Kestering, D. A., Pirkey, A. C., & Follmer, D. J. (2024). Metacognitive Intervention to Improve Problem Solving Skills in First-Year Engineering Students. *2024 ASEE Annual Conference and Exposition*.

Santiago, L. Y., Coolbaugh, A. R., & Veeramachaneni, S. S. (2016, June). Critical Thinking Skills in First-Year Engineering Students Critical Thinking Course for First Year Engineering Students. © 2016, American Society for Engineering Education. *2016 ASEE Annual Conference & Exposition*.

Santiago, L. Y., Coolbaugh, A. R., Veeramachaneni, S. S., & Morris, M. L. (2017, June). Introducing First Year Engineering Students to Engineering Reasoning. © 2017, American Society for Engineering Education. *2017 ASEE Annual Conference & Exposition*.

Schraw, G., & Dennison, R. S. (1994). Assessing Metacognitive Awareness. *Contemporary Educational Psychology*, *19*(4), 460–475. https://doi.org/https://doi.org/10.1006/ceps.1994.1033

Schuette, A. (2023). Navigating the Enrollment Cliff in Higher Education. In *Trellis Company*.

Standridge, C. R., Fleischmann, S. T., Larson, H. T., & Johnson, P. D. (2003). An Engineering Experiences Course for Non-Calculus Freshman. *Proceedings of the 2003 American Society for Engineering Education Annual Conference & Exposition*.

Stanton, J. D., Sebesta, A. J., & Dunlosky, J. (2021). Fostering metacognition to support student learning and performance. *CBE Life Sciences Education*, *20*(2). https://doi.org/10.1187/cbe.20-12-0289

Van Dyken, J., & Benson, L. (2019). Precalculus as a Death Sentence for Engineering Majors: A Case Study of How One Student Survived. *International Journal of Research in Education and Science (IJRES)*, *5*(1), 355–373. www.ijres.net

Van Dyken, J., Benson, L., & Gerard, P. (2015, June). Persistence in Engineering: Does Initial Mathematics Course Matter? *122 ASEE Annual Conference and Exposition*.

Zimmerman, B. J. (2000). Attaining Self-Regulation: A Social Cognitive Perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of Self-Regulation* (pp. 13–39). Academic Press. https://www.ebsco.com/terms-of-use

Zimmerman, B. J. (2008). Investigating Self-Regulation and Motivation: Historical Background, Methodological Developments, and Future Prospects. *Source: American Educational Research Journal*, *45*(1), 166–183. https://doi.org/10.3102/000283120

Zimmerman, B. J., & Kitsantas, A. (1997). Developmental phases in self-regulation: Shifting from process goals to outcome goals. *Journal of Educational Psychology*, *89*(1), 29–36. https://doi.org/10.1037/0022-0663.89.1.29

FIGURE LEGENDS:

Table 1: Summary of participant demographics (Control = 125, Experimental = 21). *High School GPA, Math SAT, and Math ACT scores are represented as the average ± standard deviation.

Table 2: A list of topics covered each week in the intervention course.

Figure 1: (A) Summary of total scores on the MAI survey before and after the intervention course. (B) Results from BEST statistical testing comparing the difference of means between the pre and post MAI survey scores.

Figure 2: BEST statistical testing comparing the difference of means of confidence bias between the metacognition pre- and post-tests. Results are stratified between pre and post question confidence bias (A-B vs C-D) and easy and difficult content questions (A and C vs B and D).

Figure 3: BEST statistical testing comparing the difference of means of confidence bias between the metacognition pre-test and the course final exam. Results are stratified between pre and post question confidence bias (A-B vs C-D) and easy and difficult content questions (A and C vs B and D).

Figure 4: Comparison of grade distributions between the control and experimental cohorts in their (A) trigonometry and (B) chemistry courses.

Figure 5: (A-B) Summary of (A) cumulative and (B) 1 semester GPA for the control and experimental cohorts. (C-D) Results from BEST statistical testing comparing the difference of means between the cohorts' (C) cumulative and (D) 1 semester GPA.

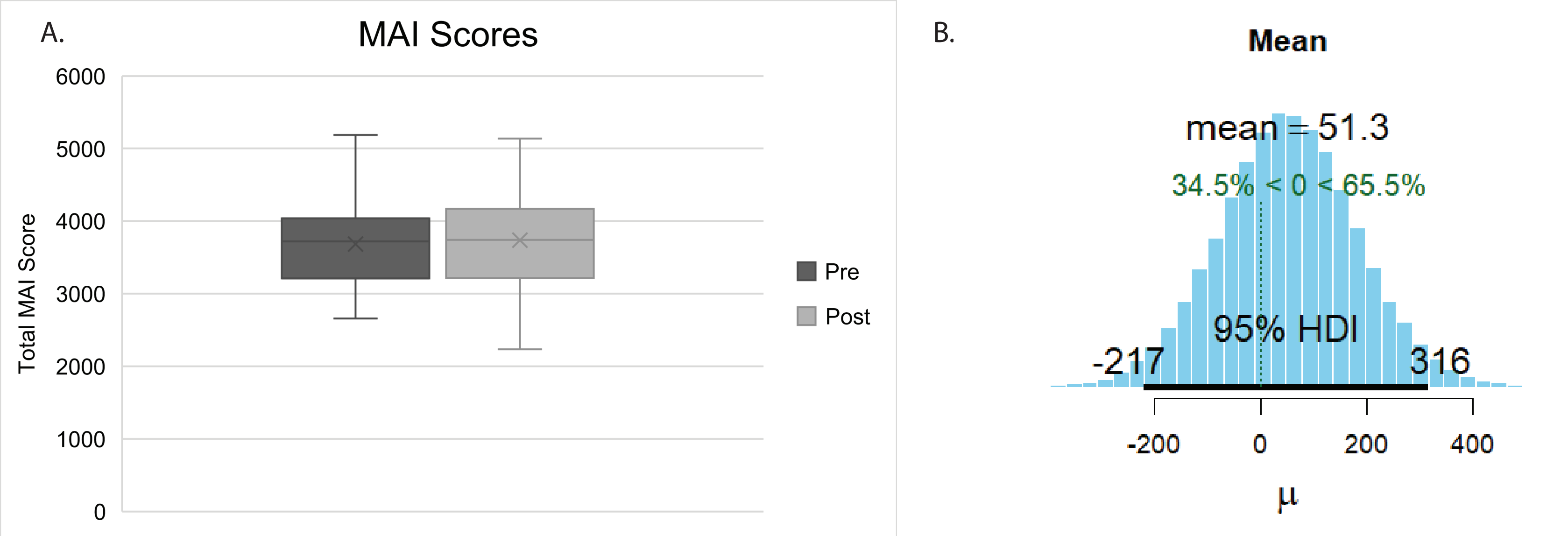
APPENDIX A: POSTERIOR DISTRIBUTIONS FROM BAYESIAN ANALYSIS

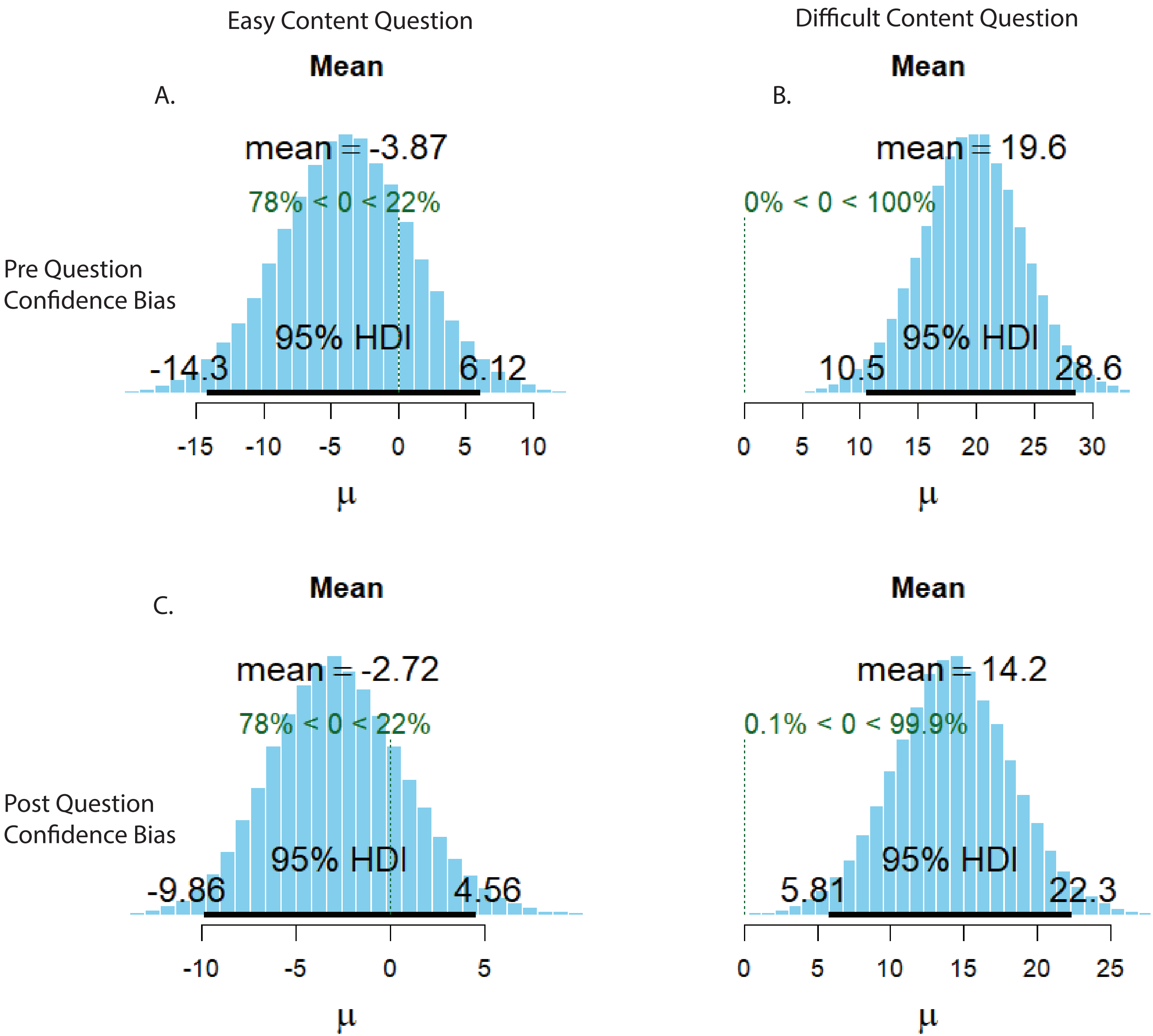
Figure S1: (A) Posterior distributions of the proportion of male students in the experimental and control groups and the posterior distribution of the percentage point difference in proportions between the two groups. (B) – (D) Results from BEST statistical testing comparing the difference of means between the experimental and control groups for (B) High School GPA, (C) Math SAT score and (D) Math ACT score.

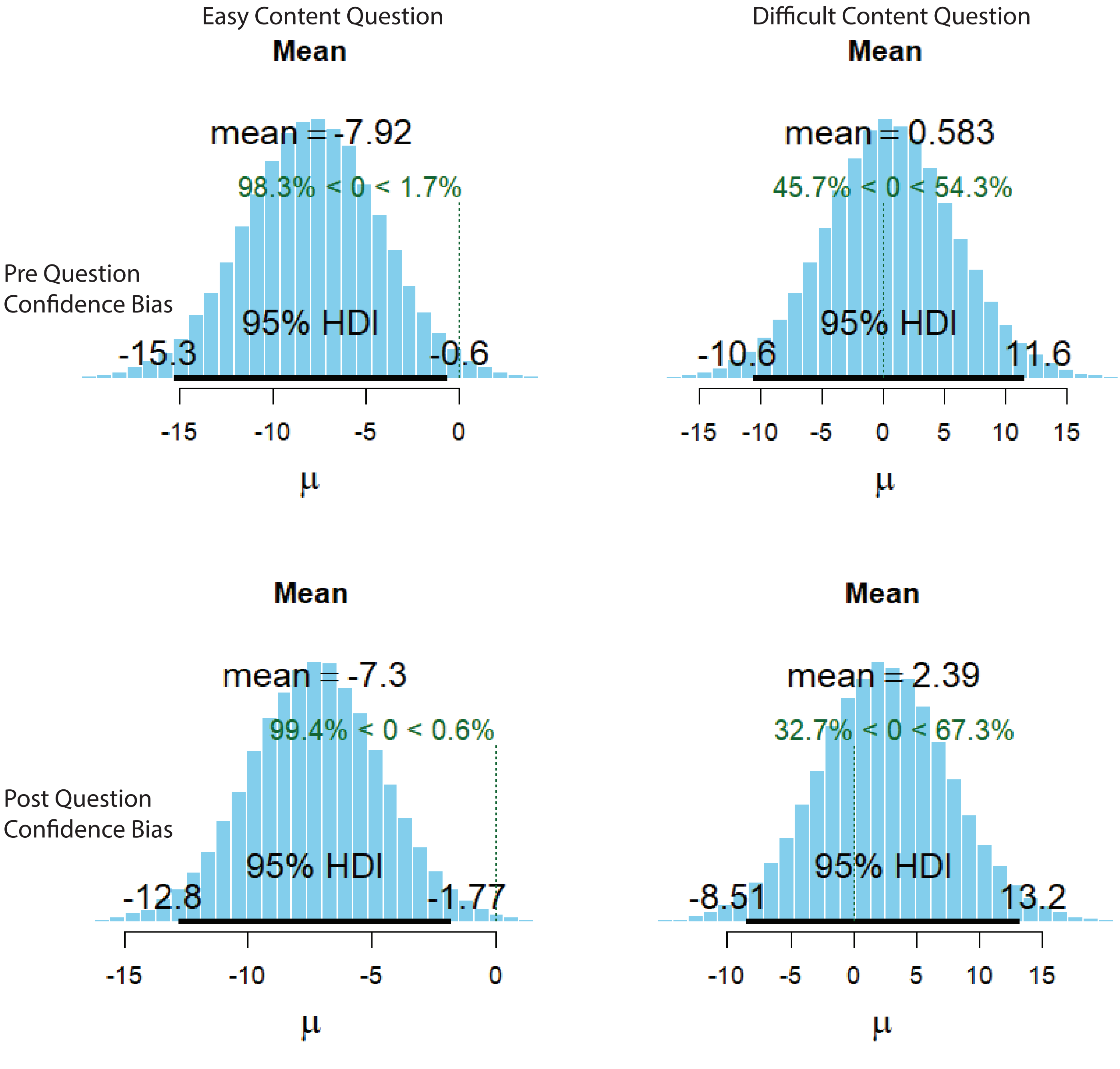
Figure S2: Posterior distributions of the proportion of students to (A) pass trigonometry (B) pass chemistry (C) receive an A in trigonometry or (D) receive an A in chemistry in the experimental and control groups and the posterior distribution of the percentage point difference in proportions between the two groups.

Characteristics of Participants				
Parameter	Control		Experimental	
Male	35	92%	20	95%
Female	3	8%	1	5%
Total	38		21	
HS cGPA*	3.84 ± 0.33		3.82 ± 0.27	
Math SAT*	560 ± 29		561 ± 29	
Math ACT*	21 ± 3		22 ± 2	

Week	Class Topic
1	Introduction and Pre-Assessments
2	Angles Linear and Angular Speed Rotation
3	Right Triangle Skills and Applications Retrieval Practice
4	Trig Functions and the Unit Circle Self Regulation
5	Applications of Trig Functions Metacognition
6	Graphing Trig Functions Graphing Applications
7	Inverse Trig Functions Review of Topics Covered to Date
8	Multistep Trig Problems Midterm Exam
9	Fundamental Identities Applications of Trigonometric Models
10	Solving Trig Equations Projectile Motion Applications
11	Hands on Application - Trusses Lab
12	Sum and Difference Formulas Skills and Applications
13	Multiple Angle and Product-to-Sum Formulas Skills and Applications
14	Law of Sines & Cosines Non-Right Triangle Applications
15	Post-Assessments and Final Exam Review

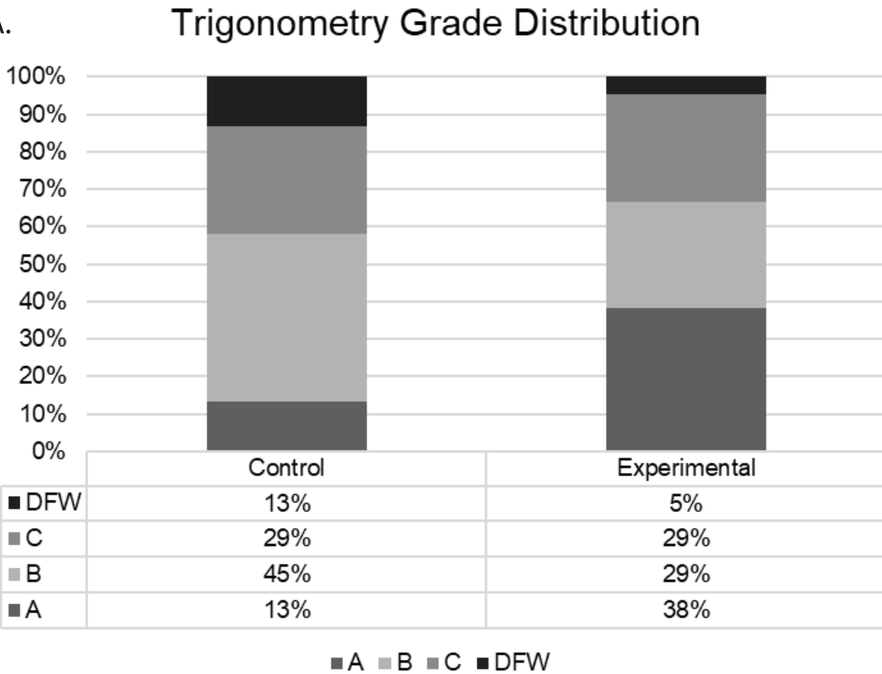

A.
MAI Scores
Total MAI Score
6000
5000
4000
3000
2000
1000
0
Pre
Post
B.
Mean
mean = 51.3
34.5% < 0 < 65.5%
95% HDI
-217
316
-200
0
200
400
μ


Easy Content Question
Difficult Content Question
Pre Question Confidence Bias
Post Question Confidence Bias
A.
Mean
mean = -3.87
78% < 0 < 22%
95% HDI
-14.3
6.12
-15
-10
-5
0
5
10
μ
B.
Mean
mean = 19.6
0% < 0 < 100%
95% HDI
10.5
28.6
0
5
10
15
20
25
30
μ
C.
Mean
mean = -2.72
78% < 0 < 22%
95% HDI
-9.86
4.56
-10
-5
0
5
μ
Mean
mean = 14.2
0.1% < 0 < 99.9%
95% HDI
5.81
22.3
0
5
10
15
20
25
μ



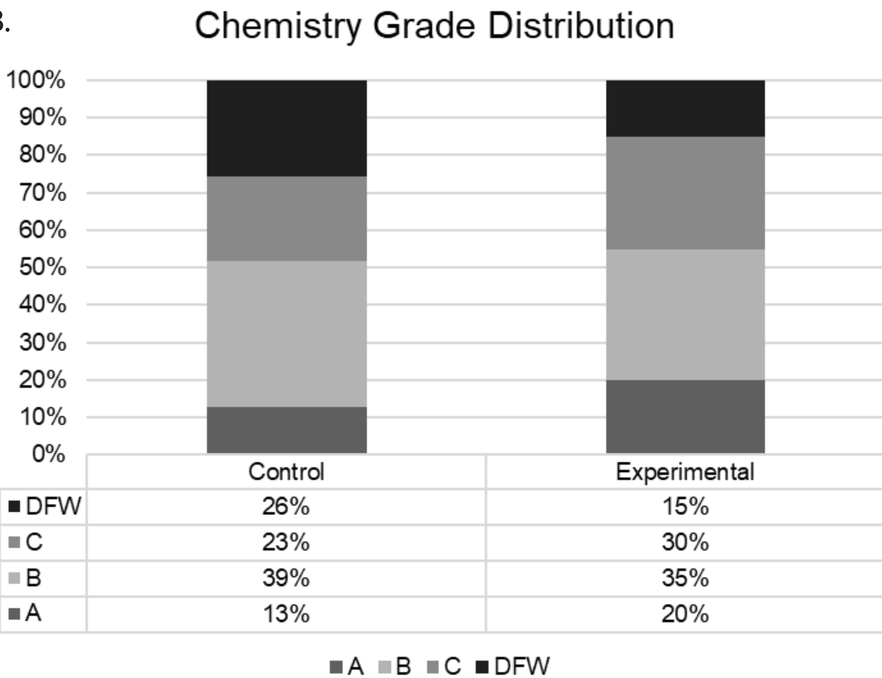
Easy Content Question
Difficult Content Question
Mean
mean = -7.92
98.3% < 0 < 1.7%
Pre Question
Confidence Bias
95% HDI
-15.3
-0.6
-15
-10
-5
0
μ
Mean
mean = 0.583
45.7% < 0 < 54.3%
95% HDI
-10.6
11.6
-15
-10
-5
0
5
10
15
μ
Mean
mean = -7.3
99.4% < 0 < 0.6%
Post Question
Confidence Bias
95% HDI
-12.8
-1.77
-15
-10
-5
0
μ
Mean
mean = 2.39
32.7% < 0 < 67.3%
95% HDI
-8.51
13.2
-10
-5
0
5
10
15
μ

A.

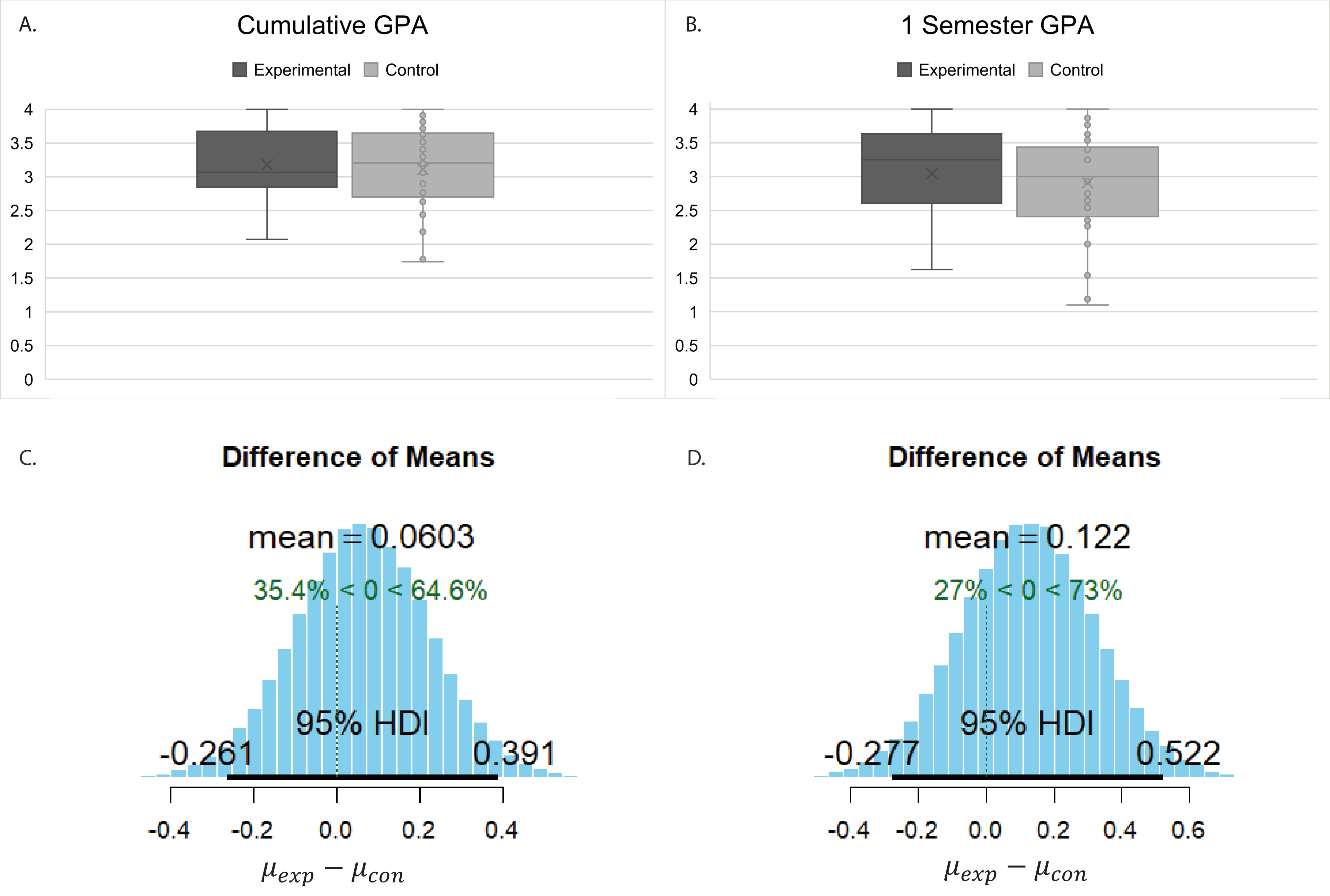


	Control	Experimental
DFW	13%	5%
C	29%	29%
B	45%	29%
A	13%	38%

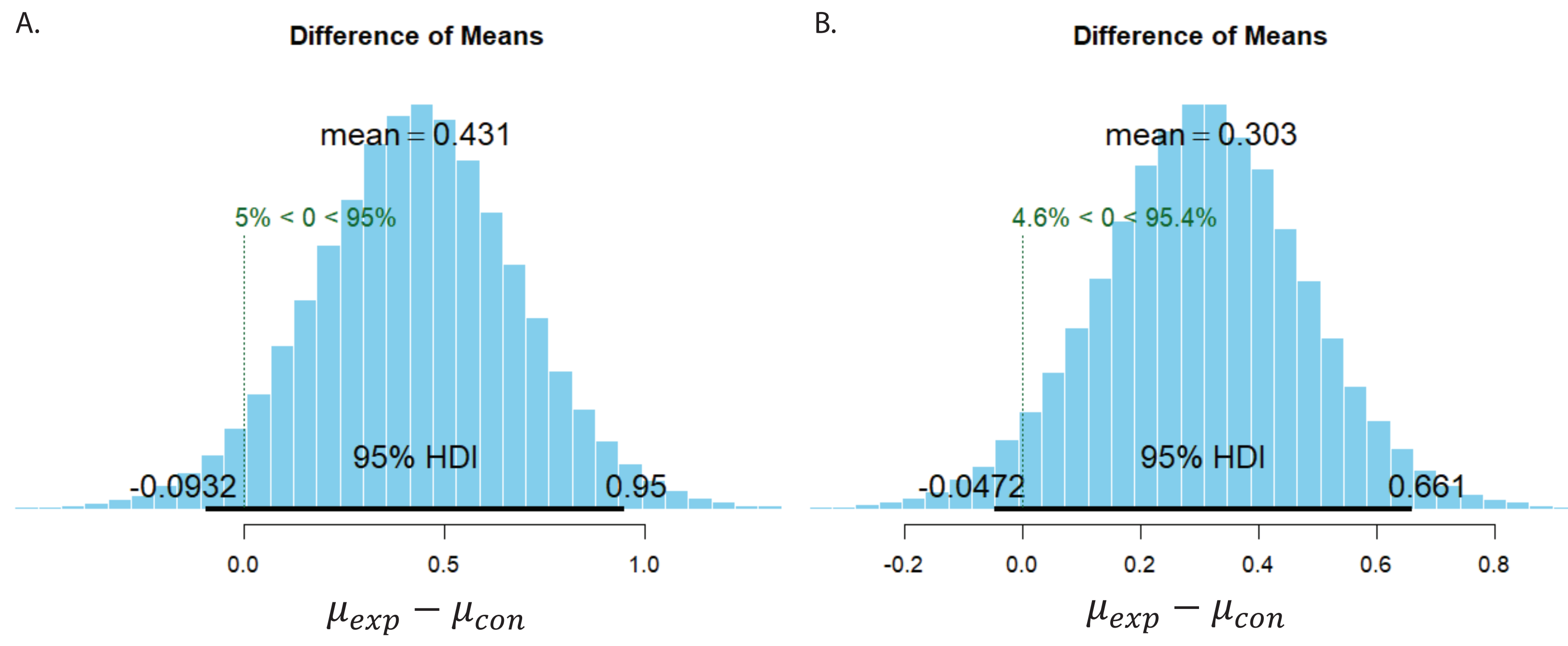
B.



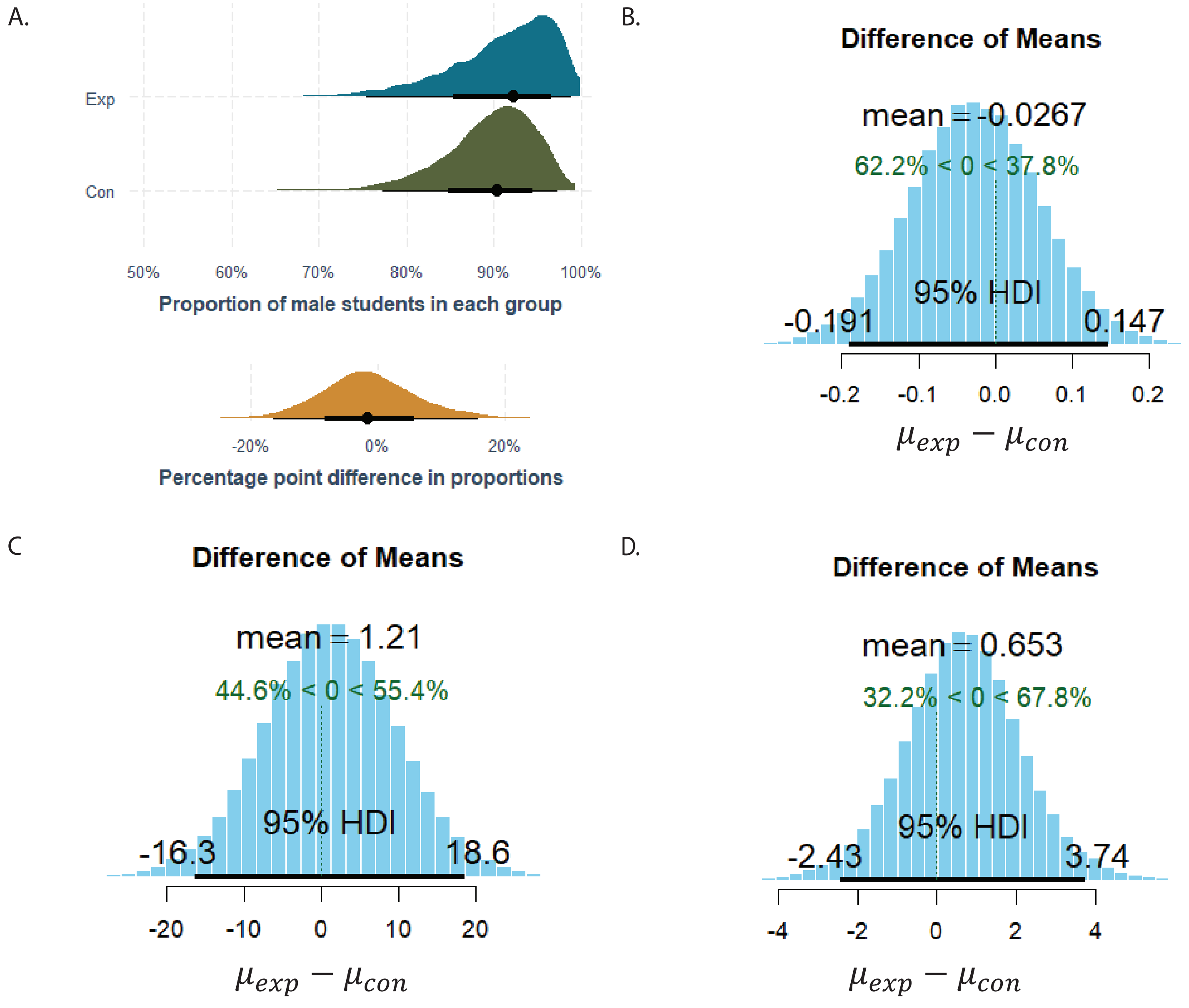
	Control	Experimental
DFW	26%	15%
C	23%	30%
B	39%	35%
A	13%	20%

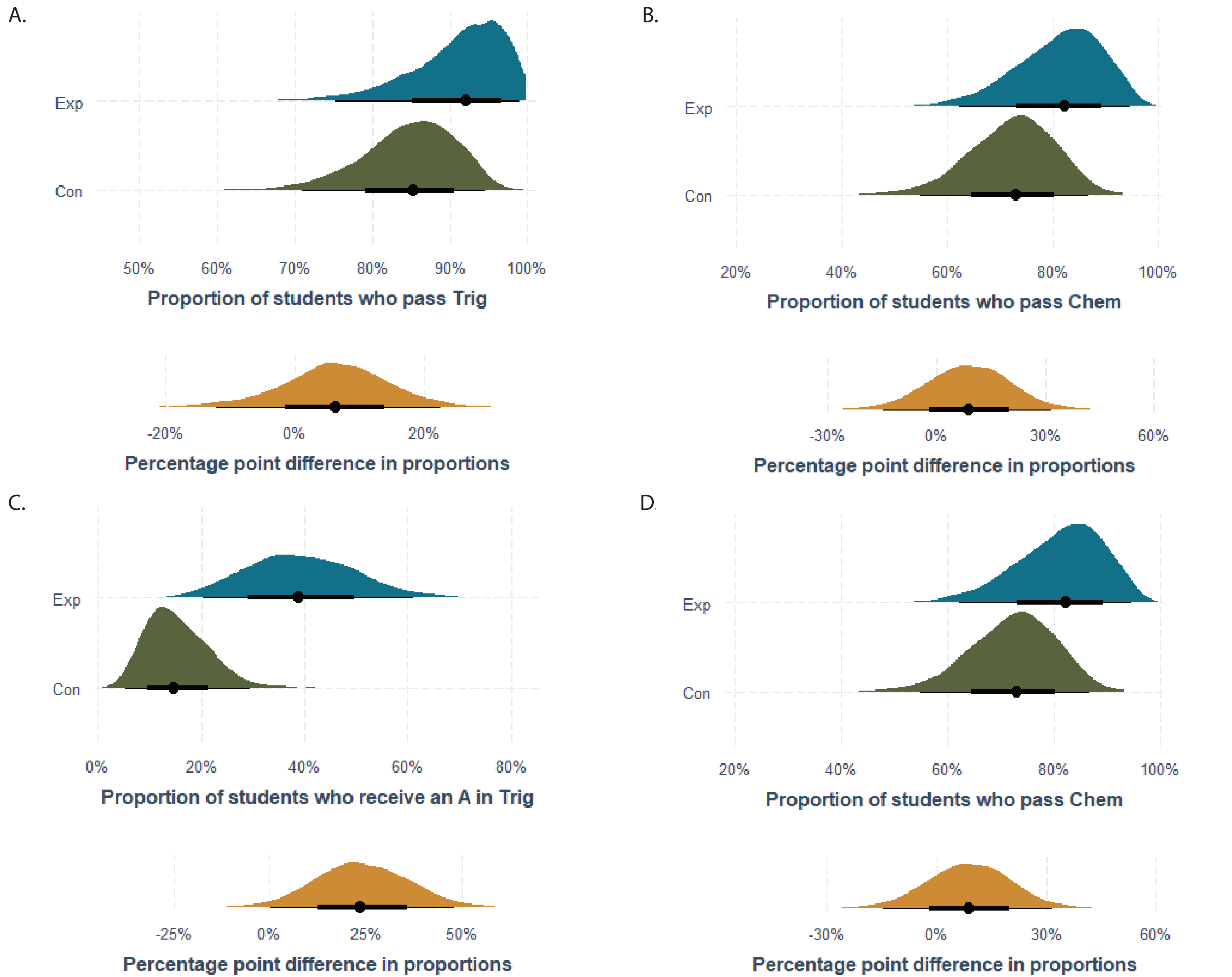


A.
Cumulative GPA
Experimental
Control
4
3.5
3
2.5
2
1.5
1
0.5
0
B.
1 Semester GPA
Experimental
Control
4
3.5
3
2.5
2
1.5
1
0.5
0
C.
Difference of Means
mean = 0.0603
35.4% < 0 < 64.6%
95% HDI
-0.261
0.391
-0.4
-0.2
0.0
0.2
0.4
$\mu_{exp} - \mu_{con}$
D.
Difference of Means
mean = 0.122
27% < 0 < 73%
95% HDI
-0.277
0.522
-0.4
-0.2
0.0
0.2
0.4
0.6
$\mu_{exp} - \mu_{con}$



A.
Difference of Means
mean = 0.431
5% < 0 < 95%
95% HDI
-0.0932
0.95
0.0
0.5
1.0
$\mu_{exp} - \mu_{con}$
B.
Difference of Means
mean = 0.303
4.6% < 0 < 95.4%
95% HDI
-0.0472
0.661
-0.2
0.0
0.2
0.4
0.6
0.8
$\mu_{exp} - \mu_{con}$


A.
Exp
Con
50%
60%
70%
80%
90%
100%
Proportion of male students in each group
-20%
0%
20%
Percentage point difference in proportions
B.
Difference of Means
mean = -0.0267
62.2% < 0 < 37.8%
95% HDI
-0.191
0.147
-0.2
-0.1
0.0
0.1
0.2
$\mu_{exp} - \mu_{con}$
C
Difference of Means
mean = 1.21
44.6% < 0 < 55.4%
95% HDI
-16.3
18.6
-20
-10
0
10
20
$\mu_{exp} - \mu_{con}$
D.
Difference of Means
mean = 0.653
32.2% < 0 < 67.8%
95% HDI
-2.43
3.74
-4
-2
0
2
4
$\mu_{exp} - \mu_{con}$


A.
Exp
Con
50%
60%
70%
80%
90%
100%
Proportion of students who pass Trig
-20%
0%
20%
Percentage point difference in proportions
B.
Exp
Con
20%
40%
60%
80%
100%
Proportion of students who pass Chem
-30%
0%
30%
60%
Percentage point difference in proportions
C.
Exp
Con
0%
20%
40%
60%
80%
Proportion of students who receive an A in Trig
-25%
0%
25%
50%
Percentage point difference in proportions
D.
Exp
Con
20%
40%
60%
80%
100%
Proportion of students who pass Chem
-30%
0%
30%
60%
Percentage point difference in proportions