

METHODS FOR LEARNING WHAT WORKS IN EDUCATIONAL TECHNOLOGY



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Abstract

Online learning platforms, such as ASSISTments, have become a major tool among teachers in the education sector. Our team looks at the Student Support Data and answers a series of research questions based on the effectiveness of requesting different student supports, like hints and explanations. This was implemented by conducting meta-analyses and using statistical analyses to draw conclusions. Due to the fact that only a few students requested tutoring, we found little to no effects between the two student supports.

Acknowledgments

We would like to express our deepest gratitude to our advisor, Professor Adam Sales, for his continuous support and guidance throughout this project.

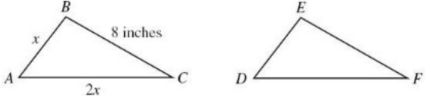
Additionally, we would like to thank the entire ASSISTments Team, specifically, Ethan Prihar and Professor Neil Heffernan for providing us the dataset and additional resources necessary for the project.

Executive Summary

Today, educational technology plays an important role in the educational sector. There are numerous platforms available for the teachers to choose from, and one such digital learning tool is ASSISTments. Developed in 2003, ASSISTments is an online learning platform which is dedicated to improving student's learning through responsible online technology. The teachers are able to assign a set of problems to each student and track their progress on assignments. If a student struggles with a problem, then they are able to request student support to help them understand the problem better. The Student Support Delivery Service offers support to students through ASSISTments tutor in the form of hints and explanations. Figure I shows a series of hints that students can see use as clues to solve the problem. As more hints appear on the screen, the less credit a student receives until the final answer is displayed at the end.

Problem 1

Triangles ABC and DEF are congruent. The perimeter of triangle ABC is 23 inches.
What is the length of side DF in triangle DEF?



Hint
Since the two triangles are congruent if you find the value of AC you will then have the value of DF.
Start by finding the value of AC.

Hint
You know the perimeter of ABC is 23 so you can set up an equation to solve to find x then use that value to find AC. The equation is:
 $x + 8 + 2x = 23$

Hint
Solve the equation
 $x + 8 + 2x = 23$
 $x + 2x = 23 - 8$
 $3x = 15$
 $x = 5$

Hint
Now that you know x you know the value of AC is $2x = 2 \cdot 5 = 10$
So the value of DF is also 10

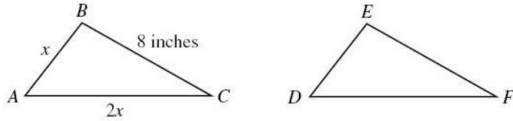
Figure I: Student Support Tutoring in Assignments: series of hints

Figure II shows how explanations are used as a student support. When a student clicks on the explanation button, a description on how to solve the problem appears with the correct answer at the bottom. A student receives no credit on the problem after requesting explanation for student tutoring.

Problem 1

Triangles ABC and DEF are congruent. The perimeter of triangle ABC is 23 inches.

What is the length of side DF in triangle DEF?



Explanation
Find AC and you will have DF since the two triangles are similar.

You can set up an equation:
Solve the equation

$$x + 8 + 2x = 23$$

$$x + 2x = 23 - 8$$

$$3x = 15$$

$$x = 5$$

Now that you know x you know the value of AC is $2x = 2 \cdot 5 = 10$
So the value of DF is also 10

Figure II: Student Support Tutoring in Assignments: full explanation of how to solve a problem

This platform has been collecting data and driven insights and providing effective feedback to students. Our team was asked to look at The Student Support Data, gathered from ASSISTments Tutor between 2018-2021, to use in this study. It contains information on all instances when a student was provided with student support, selected at random, in a high school math class.

Research Questions and Implementation

Based on the dataset, our team came up with the following objectives:

1. Calculate the effect size for each of our research questions to calculate the effects between different student supports.
2. To calculate if a student is more likely to click a hint button vs an explanation button.
3. To determine the effects of using a hint versus an explanation on students who requested tutoring.
4. To determine the effects of using a hint versus an explanation on students who answered the problem.
5. To determine the effects of using a hint versus an explanation on students who tried the next problem and asked for tutoring.
6. To determine the effects of using a hint versus an explanation on students who completed the entire assignment.
7. To determine the effects of using a hint versus an explanation on students who were shown the answer.

One of our main objectives of our project was to find the effects of using a hint versus an explanation on a student's learning. In order to successfully analyze our data for these statistics we utilized what is known as meta-analysis where the entire studies become the elements of the analysis. This means that each student that was randomized between hints and explanations was considered a study. We took the quantitative data from the studies and converted it to the numerical values to find answers to our research questions by calculating the effect size. By choosing the control group design method through odds ratio we determined the ratio of the probability of some event over the probability of a non-event which gave us the effect size for each research question. By also using the random effects model, we calculated the tau-squared for each problem by estimating the variance of the distribution of the true effect sizes. Next, we answered the non-next problem correctness questions by updating the code and calculating the odds ratio and finally, we subsetted the data by multiple variables for more accurate results.

Results and Discussion

Our results included an overview of the distribution between percentages of all the students who were assigned hints and explanations along with the percentages of previous requesters who were assigned hints and explanations. The table showed variability in the comparisons between the two categories since the percentages changed drastically for each research question. We also concluded that there are possibly small effects between the effects of hints versus explanations with little variation between studies. This was because the odds ratio and the confidence intervals were closer to 1.0 and the p-values were well above 0.05. Additionally, there are forest plots incorporated in the appendix to visually display the results for each question analyzed.

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Chapter 1: Introduction

In the age of Educational Technology, numerous teachers use online learning platforms to help their students gain more knowledge on a topic. One of those online platforms is ASSISTments. With the goal to improve student's learning, ASSISTments collects data driven insights and provides effective feedback to students. There is also an option for students to request student support to help with their homework. Through a randomized trial, ASSISTments collected Student Support Data where students were assigned student support, either in the form of a hint or an explanation. The dataset was gathered between 2018-2021 from a high school math class which included various variables corresponding to the students and the student support they received. Based on the data available, we wanted to find the following research questions:

1. What is the effect of using a hint versus an explanation on a student's learning?
2. Is a student more likely to click a hint button vs an explanation button?
3. What is the effect of using a hint versus an explanation on students who requested tutoring?
4. What is the effect of using a hint versus an explanation on students who answered the problem?
5. What is the effect of using a hint versus an explanation on students who tried the next problem and asked for tutoring?
6. What is the effect of using a hint versus an explanation on students who completed the entire assignment?

7. What is the effect of using a hint versus an explanation on students who were shown the answer?

In order to find answers to these questions, we utilized what is known as meta-analysis where the entire studies become the elements of the analysis. This means that each student that was randomized between hints and explanations was considered a study. We took the quantitative data from the studies and converted it to the numerical values to find answers to our research questions by calculating the effect size. First, we first sorted the dataset and found sample sizes to get a list of randomized experiments to analyze by downloading tidyverse and meta libraries in R studio. Next, we calculated the effect sizes by choosing the control group design method through odds ratio which determined the ratio of the probability of some event over the probability of a non-event. Using the random effects model, we calculated the tau-squared for each problem by estimating the variance of the distribution of the true effect sizes. For the next part of our methodology, we answered the non-next problem correctness questions by updating the code and calculating the odds ratio. Our final step was to subset the data by multiple variables for more accurate results. We implemented these for all our research questions and displayed the results in tables for easier comparison.

Our results section starts off with an overview of the distribution between percentages of all the students who were assigned hints and explanations along with the percentages of previous requesters who were assigned hints and explanations. The table showed variability in the comparisons between the two categories since the percentages changed drastically for each research question. We also concluded that there are possibly small effects between the effects of

hints versus explanations with little variation between studies. This was because the odds ratio and the confidence intervals were closer to 1.0 and the p-values were well above 0.05.

Additionally, there are forest plots incorporated in the appendix to visually display the results for each question analyzed.

This paper starts off with the background section where we talk about ASSISTments functionality, introduce the dataset and the set of variables that will be used for our analysis. We also explain how to interpret the dataset while providing examples of how the data is structured. Then, the paper leads to the methodology section where we thoroughly explain the steps we took to find results for the research questions. By sorting data and finding sample sizes, we then explain methods to calculate treatment effects, standard effects, and p-values. We also talk about polling effect sizes and answering non-npc questions and subsetting the data. Using the methods, our next chapter displays the results we found for each question and interpret the effect of different student supports. Based on the results we got, the paper summarizes our project and lists a number of recommendations for the future researchers to implement while conducting further research. Finally, the appendix includes all the code and the forest plots which can be useful to replicate this project.

Chapter 2: Background

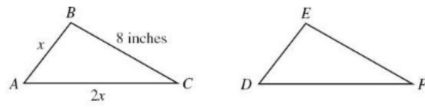
ASSISTments is an online learning platform which is dedicated to improving student's learning through responsible online technology that is “teacher-paced and evidence based” (ASSISTments, 2020). Since it was developed in 2003, this educational platform has been collecting data driven insights and providing effective feedback to students. In ASSISTments, teachers assign a sequence of problems to students. If a student struggles with a problem, then they are able to request student support to help them understand the problem better. The Student Support Delivery Service offers support to students through the ASSISTments tutor in the form of hints and explanations. It is optional for students to get support in a problem which means that support is provided for each problem, however, the students can only utilize the support if they click on the “hint” or the “explanation” button (Prihar, 2021). The Student Support Data data that will be used in this study is gathered from ASSISTments Tutor between 2018-2021. It contains information on the instances when a student was offered with student support, selected at random, in a middle school math class. Appendix 1 explains some variables from the collected dataset which will be useful for our study.

Using the dataset, we will be calculating the effect of different student supports. If a student gets randomized to receive a hint, then they are able to get partial credit on the problem by using a hint as a resource to answer the problem. For instance, Figure 1 displays a set of hints for one particular math problem. Students are able to click on the hint button again to get each hint in the sequence, until all the hints are shown. Each hint will help students get to the right answer by providing a series of clues. The more hints the students select, the less credit they receive until the last hint, which displays the final answer, where no credit is given to the students.

Problem 1

Triangles ABC and DEF are congruent. The perimeter of triangle ABC is 23 inches.

What is the length of side DF in triangle DEF?



Hint
Since the two triangles are congruent if you find the value of AC you will then have the value of DF. Start by finding the value of AC.

Hint
You know the perimeter of ABC is 23 so you can set up an equation to solve to find x then use that value to find AC. The equation is:
 $x + 8 + 2x = 23$

Hint
Solve the equation
 $x + 8 + 2x = 23$
 $x + 2x = 23 - 8$
 $3x = 15$
 $x = 5$

Hint
Now that you know x you know the value of AC is $2x = 2 \cdot 5 = 10$
So the value of DF is also 10

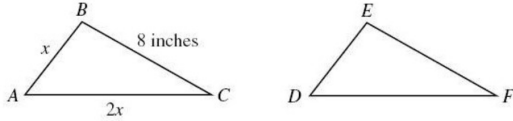
Figure 1: Student Support Tutoring in Assignments: series of hints

Figure 2, on the other hand, is an example of an explanation on the same math problems. It only displays the final answer along with helpful descriptions or visual tools to help students understand the problem. When a student chooses to select an explanation, then they receive no credit on the problem. The explanations provide all the information to solve the problem at once. Hints, however, break it up into different parts and only show students additional information when requested.

Problem 1

Triangles ABC and DEF are congruent. The perimeter of triangle ABC is 23 inches.

What is the length of side DF in triangle DEF?



Explanation
Find AC and you will have DF since the two triangles are similar.

You can set up an equation:
Solve the equation

$$x + 8 + 2x = 23$$

$$x + 2x = 23 - 8$$

$$3x = 15$$

$$x = 5$$

Now that you know x you know the value of AC is $2x = 2 \cdot 5 = 10$
So the value of DF is also 10

[Figure 2: Student Support Tutoring in Assignments: full explanation of how to solve a problem](#)

We are interested in the relative effect of hints and explanations by measuring the effects using measurements of students' behavior within the system. We are primarily interested in whether they correctly answer the next problem they work on the first try. Formally, The next problem-correctness of the students also can be interpreted if the students receive the hint and don't attempt the next problem and request tutoring again, then npc is 0. The students need to get the next problem right in the first attempt for the npc to be 1. Figures 1 & 2 explain the difference between the two student supports on ASSISTments.

The table below also includes a set of *student support features* which co-relate with the student_support logs including each student's support id, and student support they received. In this paper, we used some of these variables to find the effectiveness between different student support features. The ones that are primarily important for our research questions are the student support id, the student support is hint, and the student support is explanation.

student_support_features	This table contains the features of the student supports referenced in student_support_logs.csv.
student_support_id	The ID of the student support.
student_support_content_creator_id	The ID of the creator of the student support i.e whoever wrote the hint or explanation
student_support_is_hint	A flag that indicates that the student support is a hint. Hints are a series of messages that the user requests, one at a time, that each explain part of how to reach the answer without providing the answer.
student_support_is_explanation	A flag that indicates that the student supports is an explanation. An explanation is a single message that the user requests, which explains how to solve the problem and provides the answer.
student_support_message_count	The number of messages in the hint or explanation. This value will always be 1 for explanations.
student_support_text_length	The character count of the text of the student support.

These variables in the dataset can be interpreted using Figure 3. For example, a student with the `student_support_id` 1148580, was randomized between student supports. Since the `student_support_is_hint` column for that student has a 1, it means that the student was randomly chosen to receive a hint. The 0 in the `student_support_is_explanation` means that the student was not offered an explanation for the problem. Since the student received a hint, the number 2 in the `student_support_message_count` means that the student received two hints for the question with the text length of 203.

	student_support_features							
	student_support_id	student_support_content_creator_id	student_support_is_hint	student_support_is_explanation	student_support_message_count	student_support_text_length	student_support_contains_video	student_support
1								
2	1148416	436919	0	1	1	0	1	
3	1148417	436919	0	1	1	0	1	
4	1148418	436919	0	1	1	0	1	
5	1148419	436919	0	1	1	0	1	
6	1148432	436919	0	1	1	6	1	
7	1148433	436919	0	1	1	6	1	
8	1148475	436919	0	1	1	6	1	
9	1148493	436919	0	1	1	6	1	
10	1148494	436919	0	1	1	6	1	
11	1148495	436919	0	1	1	6	1	
12	1148569	460570	0	1	1	180	0	
13	1148571	460570	0	1	1	258	0	
14	1148572	460570	0	1	1	459	0	
15	1148573	460570	0	1	1	787	0	
16	1148574	460570	0	1	1	324	0	
17	1148575	460570	0	1	1	137	0	
18	1148578	460570	0	1	1	473	0	
19	1148580	460571	1	0	2	203	0	
20	1148581	460571	1	0	2	174	0	
21	1148582	460571	1	0	1	97	0	
22	1148583	460571	1	0	2	371	0	
23	1148584	460571	1	0	2	165	0	
24	1148585	460571	1	0	1	90	0	
25	1148588	460571	1	0	1	54	0	
26	1148670	436919	0	1	1	6	1	

Figure 3: Student Support Features Dataset Interpretation

In our study we decided to compare the data of all the students randomized between a specific set of student supports. By analyzing the data across these supports for significant statistics, we hope to be able to answer many questions related to student learning. The research questions we attempt to answer are mentioned in the previous section. The following is a table of

variables that were used in order to answer our list of research questions related to the next problem.

Research Question	Variable Used	Description
Did the students click on the hint button?	tutoring_observed	This variable indicates that the student observed a student support or, when the student was given just the answer, that they observed the answer.
Did they actually put in the answer?	problem_completed	This variable indicates that the student completed the problem that the selected student support was provided for.
Did they do the next problem and ask for tutoring?	try_next	This variable indicates if the student attempted to do the next problem or if they asked for tutoring by clicking on the hint or the explanation button.
Did they complete the entire assignment?	assignment_completed	This variable indicates that the student completed their assignment.
Did they receive all the hints?	answer_given	This variable indicates that a student was provided with the

		<p>answer. If the student support provided to the student was an explanation, or the student was only given the answer, then this flag and the previous flag will be identical. However, if the student support provided to the student was a hint, then when the student observed some of the hints, but not the final hint, which provides the answer, this flag will be 0 while the previous flag is 1.</p>
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Meta-Analysis

In order to successfully analyze our data for these statistics we utilized what is known as meta-analysis. In meta-analysis, entire studies become the elements for analysis (Harrer, 2021). In our case, each work problem where students were randomized between a hint and an explanation is considered a study. We can then take quantitative data from these studies and get numerical values that will answer our research questions. In order to convert our data to these numerical values, we will have to find effect size across all studies. The effect size is defined in different ways depending on who you ask. We think of it in relation to a treatment and control group, where the effect size is considered the effect of a treatment and how large that treatment is. While all this may seem simple enough, using meta-analysis means you will run into some problems along the way. This is because meta-analysis will help us derive general conclusions

from a group of studies by estimating average effects across studies. We will also be able to estimate the variance of effects across studies to calculate the effect between different student supports like hints and explanations with additional student support features.

One of the major issues with using meta-analysis is the fact that there could be bias. Since entire studies are the elements of analysis, this could mean that any number of the studies examined may have been tampered with or written up by someone who is biased towards a specific result. To solve this problem you just have to be aware of which articles you are including in your list of studies. However, we are including all randomized hints and explanations comparisons within ASSISTments of a certain sample size. We are not including other data on similar projects already performed in this field. This means that bias will not be a problem in our project.

Summaries of Papers Read in A-term

Prior to conducting any calculations, we read some research papers in the first part of our research. These papers were based on the past studies on ASSISTments. It gave us more information about the learning platform and the methodology used to draw conclusions in the related field. The paper, “Toward Personalizing Students’ Education with Crowdsourcing Tutoring”, (Prihar et al., 2021) focuses on crowdsourcing tutoring from teachers and exploring data from TeacherASSISTments. The dataset consists of features like using crowdsourcing methods to collect tutoring questions from a variety of teachers, and comparing different school

years data to measure accuracy. The paper's mission is to answer the following research questions: Do the findings on the effects of some teachers' content over others, of the previous TeacherASSIST study, still hold when tested on new data? How did the effect of teachers' tutoring compare to each other? Was there any potential to personalize the tutoring students received based on their knowledge-level? The authors answer these questions by doing an experiment on students with some taking tests in a control environment with no option to request tutoring, while others receiving intent-to-treat conditions where they have the option but they do not request tutoring. This condition is the same as what we worked with. The students had the option of requesting tutoring, but not everyone actually requested any. Majority of the students assigned to the treatment condition have a reliable positive effect. The variance covariance method is also used to compare the effects of different teacher's tutoring and potential personalized tutoring. Using the methodology, the paper concludes that teacherASSIST has overall positive results on students and it opens up the findings by talking about how this research can be used to answer further questions (Prihar et al., 2021).

The "Automatic Interpretable Personalized Learning" paper ASSISTments's Automatic Personalized Learning Service (APLS)" (Prihar et al., 2022), which personalizes the content based on what's going to be most helpful for the student by using multi armed bandit method: "Used to adjust how often students receive support option by estimating each option's effectiveness and intentionally giving more students with most effective option"(Prihar et al., 2022, p.1). Utilizing crowdsourcing and randomized control methods, the paper's focus is to answer if different algorithms were used such as Decision Tree Thompson Sampling (DTTS) would it have a positive effect on personalized learning? ASSISTments had not used DTTS at

the time. Instead it used APLS online and offline methods. The APLS online method when the information is used from the algorithm to predict which student support is likely to have the most positive effect on learning and sends it to ASSISTments tutor. The APLS offline method uses students' actions and reviews it to update the bandit models. It allows the APLS to learn over time how to most effectively personalize students' learning. APLS also uses the Beta-Bernoulli Thompson Sampling (BBTS) is a simple contextual bandit algorithm for environments with binary rewards. To determine if DTTS is the better option, 3 simulations were implemented where DTTS used a CART decision tree. The first simulation gives insight into how DTTS would have performed compared to random selection and popular multi-armed bandit algorithms over the course of a full year” (Prihar et al., 2022, p.7). Additionally, the second and the third simulation focused on “how capable DTTS is of generalizing its insight to new content” (ibid). In the end, it was concluded that DTTS has a significant enough of an impact in helping to personalize student learning that it would be added to APLS soon after the publishing of the paper.

Chapter 3: Methodology

In meta analysis, the first part is to estimate the effect in each study by choosing and estimating effect sizes. Then, we aggregate the estimated effect sizes to get an overall average effect, which assesses the variability between the studies.

1. Sorting data and finding sample sizes

The first step of our methodology was to download the tidyverse and meta libraries in R. This was important to conduct the rest of the analysis. Next, we downloaded “HintVSexplbig.RData” which contained the results from the experiments conducted in ASSISTments. In order to answer our research questions, we first had to sort through the data set to get a list of randomized experiments to analyze. We did this by outputting the total number of students who were given the hint vs the explanation for all experiments.

2. Getting treatment effects, standard effects and P-values

a. Calculating Effect Size

An effect size is a metric quantifying the relationship between the two entities. In this paper, the effect size reflects the treatment effect in a particular study. Effect sizes are in standardized units, so they can be compared across studies with different outcomes. Since we want to know the effect of using a hint versus an explanation on a student’s learning, we started off by calculating the effect size for hints versus the explanations. There is a choice in what type of effect size we can use, dependent on both the interpretability and statistical properties. The two ways to calculate effect size are Single Group Designs and Control Group

Designs. We decided to choose the control group design method over the single group. This is because Control Group Designs include experimental studies or controlled clinical trials. Single Group, on the other hand, incorporates naturalistic studies, surveys and uncontrolled trials. In our case, each student received a hint or an explanation in a randomized controlled experiment. So, Control Group Designs was the better option. Next, we wrote code in R to calculate the treatment effects and then later effect sizes.

b. Logistic Regression

Logistic Regression is similar to linear regression however, “to model binary data, we need to add two features to the base model $y = a + bx$: a nonlinear transformation that bounds the output between 0 and 1 (unlike $a + bx$, which is unbounded), and a model that treats the resulting numbers as probabilities and maps them into random binary outcomes” (Harrer et al., 2021). Thus, in a logistic regression model, the binary outcome y is a discretized version of an unobserved or latent continuous measurement z . This model is a more precise method to estimate the parameters of a logistic model, and is used specifically for a binary outcome, such as “next problem correctness”. We used this approach to help our understanding of all the treatment effects, standard errors, and p-values for all experiments before using the pooling method. This can be found in our code below.

```
betaSE <- NULL
for(rr in unique(hintVSexplbig$rand)){
  dat1 <- filter(hintVSexplbig, rand==rr)
  mod <- glm(formula = npc ~ selectedHint, family = binomial, data = dat1)
  betaSE <- rbind(betaSE,
                  summary(mod)$coef['selectedHintTRUE',]
                )
}
```


c. Odds Ratio

One of the various types of effect sizes under Control Group Designs is the odds ratio (OR). One of the only disadvantages to an odds ratio is that it is poorly understood. Thus we will define what odds and the odds ratio are. Odds are the ratio of the probability of some event to the probability of a non-event, not the probability of an event which it can be confused for. So say that a group of 3 people experienced the event and a group of 2 people did not. The probability of the event would be $\frac{3}{5}$ or 60% while the odds would be $\frac{3}{2}$ or 3 events for every 2 non-events. To calculate an odds ratio we need to use our treatment and control group, which in our study we chose the treatment to be students given hints while students given explanations were in the control. The formula below shows the formal definition of an odds ratio.

$$OR = \frac{\textit{treatment odds}}{\textit{control odds}}$$

The perfect ratio between events and non-events is when the odds ratio is 1. This means there would be no effect as the odds of both groups are the same. Anything greater than 1 signifies that the treatment has an effect on the event, and anything less than 1 signifies that the control has an effect. In order to determine if there was an effect on student learning between the two groups we decided to view the odds ratios of specific events. The events that were analyzed were next problem correctness, clicking of the hint or explanation button, putting in an answer, completion of the assignment, and receiving all hints.

The reason we chose to calculate our effect sizes with odds ratios is because they have some advantages over the other effect size types. One of these advantages is that we can scale them up or down without having to worry about hitting an upper boundary since the odds ratio can go up to infinity with a lower bound of 0.

Probabilities, on the other hand, have a lower bound of 0 and an upper bound of 1.

d. Standard Error

When we sample the population we hope to measure an estimate of the true effect on the population when in reality this could be skewed. This results in the standard error being applied, which is the standard deviation of the estimated effect if the experiment were repeated many times. In our project we do not have any sampling since we have all of our individual studies, but even in this case there will be some form of uncertainty measured by the standard error. This uncertainty comes from estimating the treatment effect in each study and when the studies are pooled together (discussed more in section 3). Since we are using the odds ratio, we must calculate the standard error of each effect size we calculate. It is common for odds ratios to be transformed to log-odds ratios to produce better results. Hence, the formula to calculate the standard error of the log-odds ratio is below.

$$SE_{\log OR} = \sqrt{\frac{1}{a} + \frac{1}{b} + \frac{1}{c} + \frac{1}{d}}$$

Variable	Value
<i>a</i>	Number of people in treatment group who had the event occur

b	Number of people in treatment group who had the non-event occur
c	Number of people in control group who had the event occur
d	Number of people in control group who had the non-event occur

The standard error of each effect size is calculated automatically when we calculate the variance for Tau-Squared, which is discussed in section 3B.

3. Pooling Effect Sizes

a. **Random Effects vs. Fixed Effects Model**

There are two different kinds of models that can be followed when performing meta analysis. These models are the fixed effects model and the random effects model. For our research, we chose the random effects model over the fixed effects model. This is because in the Random Effects Model, there's always some degree of between-study heterogeneity that can virtually always be anticipated. It pays more attention to small studies which can cause biases however, we don't need to worry about that in our data since only large studies were included which eliminates the bias of one study over another. The Fixed Effects Model is not the best option for us because it can only be used when we could not detect any between-study heterogeneity and when the true effect is fixed. In the Random Effects Model θ_k is a study k 's true effect size which is calculated using the formula below where μ is the mean of the effect size and ζ_k is the difference of study k from other studies.

$$\theta_k = \mu + \zeta_k$$

Using this formula, we get our Random Effects Formula below which looks at the observed effect size of the pooled studies where $\hat{\theta}_k$ represents the observed effect size, θ_k is a study k's true effect effect size and ϵ_k is the sampling error.

$$\hat{\theta}_k = \theta_k + \epsilon_k$$

The Fixed Effects Model can be represented by the formula below where $\hat{\theta}_k$ represents the observed effect size which deviates from θ and ϵ_k is the sampling error.

$$\hat{\theta}_k = \theta + \epsilon_k$$

The only difference between the two formulas is that the Fixed Effects Model contains θ instead of θ_k . This is because when k is dropped, θ represents the true effect size.

The model below illustrates the parameters of the random effects model. As mentioned previously, $\hat{\theta}_k$ represents the observed effect size, θ_k is a study k's true effect effect size and ϵ_k is the sampling error, ζ_k represents how study k is different from other studies. This occurs due to the fact that the true effect size of study k is part of an overarching distribution of the true effect sizes with the mean

μ . It can be clearly seen that the observed effect size steers away from the pooled effect size μ due to the two error terms, ϵ_k and ζ_k .

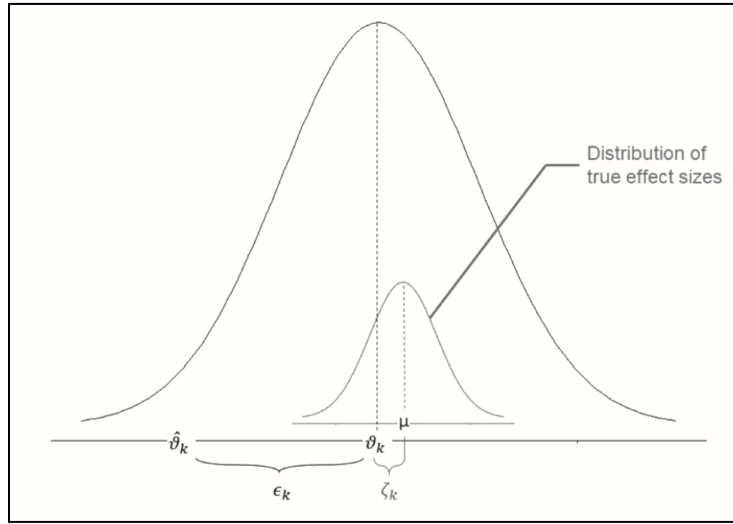


Figure 4: Parameters of random-effects model

b. Bakbergenuly-sample size method

Also known as the sample size method, Bakbergenuly-sample size method is a fairly new pooling method. In the Bakbergenuly weighted average formula, each study's effect size ($\hat{\theta}_k$) is multiplied with its corresponding weight (w_k), which is then divided by the sum of all the weights.

$$\hat{\theta} = \frac{\sum_{k=1}^K \hat{\theta}_k w_k}{\sum_{k=1}^K w_k}$$

This is an important formula to calculate the average effects in meta-analyses. The formula states that we only need to know the sample size and $n_{\text{treat}k}$ and $n_{\text{control}k}$ in control and treatment groups to determine the weight of the studies k . The weight is related to a study's precision. It depends on the total number of people in each condition of the study. (Bastian, 2017).

“When we implement this pooling method in metabin, the weights and overall effect using the fixed- and random-effects model will be identical. Only the p-value and confidence interval of the pooled effect will differ” (Harrer et al. 2021). We think that the Bakbergenuly-sample size method is better than the Mantel-Haenszel Method and Peto Method because the Mantel-Haenszel Method uses the number of events and non-events in the treatment and control group to determine a study's weight. Since this method uses continuity corrections, this method can lead to biased results. The Peto method, on the other hand, has multiple limitations. This method only works well when the number of observations in the treatment and control group is similar, when the observed event is rare (<1%), and when the treatment effect is not overly large. In the Bakbergenuly weighted average formula, each study's effect size ($\hat{\theta}_k$) is multiplied with its corresponding weight (w_k), which is then divided by the sum of all the weights.

$$\hat{\theta} = \frac{\sum_{k=1}^K \hat{\theta}_k w_k}{\sum_{k=1}^K w_k}$$

This is an important formula to calculate the average effects in meta-analyses.

c. Calculating Tau-Squared

Since we decided to use the random effects model, it is important to take the error into account. This can be done by estimating the variance of the distribution of the true effect sizes, which is known as Tau-Squared (τ^2). Below is the equation used to estimate τ^2 using a method known as (“REML”), Restricted Maximum Likelihood (Viechtbauer, W., 2005).

$\hat{\sigma}_\theta^{2(REML)}$	REML tau-squared estimator
W_i	Values of weights i where $i = 1, \dots, k$
ES_i/θ_k	Effect size estimates where $i = 1, \dots, k$
$\hat{\mu}_\theta^{(ML)}$	Mean of maximum likelihood

$$\hat{\sigma}_\theta^{2(REML)} = \frac{\sum_{i=1}^k w_i^2 \left[(ES_i - \hat{\mu}_\theta^{(ML)})^2 - \sigma_{\epsilon_i}^2 \right]}{\sum_{i=1}^k w_i^2} + \frac{1}{\sum_{i=1}^k w_i}$$

It is hard to estimate the variance and calculate τ^2 by hand, so we used the functions in the {meta} package to help answer our research questions for our analysis. The code for Tau-Squared can be found in the appendix which uses Restricted Maximum Likelihood. We found this by using the argument *method.tau* which defines the τ^2 estimator.

```

##
## Number of studies combined: k = 101
## Number of observations: o = 214107
## Number of events: e = 133819
##
##
##              OR              95%-CI    z p-value
## Random effects model 1.0177 [0.9967; 1.0392] 1.65 0.0995
##
## Quantifying heterogeneity:
## tau^2 = 0 [0.0000; 0.0038]; tau = 0 [0.0000; 0.0617]
## I^2 = 0.9% [0.0%; 25.0%]; H = 1.00 [1.00; 1.15]
##
## Test of heterogeneity:
##      Q d.f. p-value
## 100.94 100 0.4549
##
## Details on meta-analytical method:
## - Sample size method
## - Restricted maximum-likelihood estimator for tau^2
## - Q-Profile method for confidence interval of tau^2 and tau

```

The code above explains how the τ^2 estimator is used to quantify heterogeneity. The estimated heterogeneity is $\tau^2 = 0$. The percentage of variation across effect sizes that is due to heterogeneity rather than change is estimated at $I^2 = 0.9\%$.

4. Answering Non-NPC Questions

Up to this point we have been discussing the means we went about calculating the odds ratio using next problem correctness (NPC) that tells us whether hints, explanations, or both types of student support are the best for improving student learning. However there were other kinds of questions that we wished to examine, and a lot of these questions would need variables other than NPC to calculate the odds ratios for. These variables can be found in the table below.

Variable Used	Description
tutoring_observed	This variable indicates whether or not the students requested tutoring. It includes both hints and explanations.
problem_completed	This variable indicated if the student put an answer for the question. It doesn't take into account if the problem was correct or incorrect.
tryNext	This variable indicated if the students tried the next problem and asked for tutoring.
assignment_completed	This variable indicated if the student completed the entire assignment by answering all the required questions.
answer_given	This variable indicates if the student received all the hints on a problem and was given the final answer.

To calculate the new odds ratios we just had to take the code we used for the previous question and replace all instances of NPC with the other variable. We used this method because the main outcome is not the next problem. Instead, it is anything that happens after the treatment.

5. Variables used for Subsetting

Our final step in the methodology was to subset the data by using multiple variables or adding the “user” variables for more accurate results. For example, if we want to subset students who requested tutoring when evaluating the next problem correctness between hints vs explanations, then we used the code below where we added “tutoring_observed”.

```
sampleSizes <-
hintVSexplbig%>%group_by(rand)%>%summarize(n=n(),n.e=sum(selectedHint &
tutoring_observed == 1), event.e=sum(npc[selectedHint & tutoring_observed
== 1]), n.c=sum(selectedExpl & tutoring_observed == 1),
event.c=sum(npc[selectedExpl & tutoring_observed == 1]))
```

If we had to remove the cases of students who have never requested tutoring, then we used the “user_avg_support_requested” to give us a more reliable answer to our research question. An example of this can be seen in the code below.

```
dat1 <- filter(hintVSexplbig, user_avg_support_requested != 0)
sampleSizes <-
dat1%>%group_by(rand)%>%summarize(n=n(), n.e=sum(selectedHint),
event.e=sum(npc[selectedHint]), n.c=n-n.e, event.c=sum(npc[selectedExpl]))
```

Problems with Subsetting

When subsetting our data in an attempt to get more accurate results we have to be very careful. The variable used in the first snippet of code (tutoring_observed) is unreliable to use in a logistic regression as it can result in a biased subset of the population. Thus trying to run a regression with a subset of students who all clicked the button would be biased. Another reason this variable is unreliable is it was collected during the experiment and is not some previous statistic like what the “user” variables contain. Even though the results would be biased we were still curious to see what would happen if we ran the regression on it anyways, which is why the code example above is using it. To understand the bias in this situation better we must look at the problem more generally.

Each student will always fall into 1 of 4 different categories. The diagram in Figure 5 below illustrates this:

		Would Request Explanation Tutoring	
		No	Yes
Would Request Hint Tutoring	No	Never-taker	Defier
	Yes	Complier	Always-taker

Figure 5: Categories a student falls into

The main problem here is there are many outside factors that could be affecting the weight of these categories that would skew our results from the true effect. One of these factors is that students who are assigned explanations are going to be less likely to click on the button due to the fact that it will negate any credit they can receive on a problem. A hint will still give partial credit based on how many you have gone through for that problem, making it more likely for students assigned hints to be clicking the button. If we knew that we only had people in the experiments who were Never-takers and Always-takers, then there would be no problems subsetting by the tutoring_observed variable.

We used these steps to answer all our research questions.

Chapter 4: Results

<u>Results Overview</u>	Assigned Hints (All Students)	Assigned Explanations (All Students)	Assigned Hints (Previous Requesters)	Assigned Explanations (Previous Requesters)
% NPC	62.7	62.3	62.6	62.2
% Tutoring Observed	18.5	17.4	18.6	17.6
% NPC Tutoring Observed	32.5	31.6	32.5	31.5
% Problem Completed	97.4	97.4	97.4	97.4
% Tried Next Problem	95.7	95.7	95.7	95.8
% Assignment Completed	89.9	89.9	90	90
% Answer Given	13.8	17.4	13.9	17.6

As shown in the table above, the results of research questions 4-6 showed no apparent differences between the students assigned hints and students assigned explanations. The remaining 4 research questions leaned towards one side or the other. Some of these are smaller leans like for next problem correctness where 62.6-62.7% of students who were assigned hints on a problem got the next problem right compared to the 62.2-62.3% for those assigned explanations. The tutoring observed results also had a small lean towards students assigned hints where 18.5-18.6% of them clicked the student support button. The research question pertaining to the answer being given provides an example of a much larger lean in this case towards

explanations. This makes sense as the variable for this question will only return true for hints if the student actually read all the hints. However, since students will get partial credit if they do not read all the hints, this leads to bias towards explanations. These distributions are just a small overview, more in depth information can be found for each of our research questions below. Each research question that was analyzed also had a forest plot generated with it to visually display the data. These forest plots can be found in the Appendix.

RQ 1: Effect on Next Problem Correctness

<u>Results</u>	Number of studies	Number of students observed	Number of students with npc	Odds Ratio with 95% confidence interval	P-Value	Tau²
All students	101	214,107	133,819	1.0177 [0.9967; 1.0392]	0.0995	0
Previous requesters	101	194,220	121,148	1.0228 [1.0004; 1.0457]	0.0462	0.0003

The effects on Next Problem Correctness looks at 101 ASSISTments problems. There are a total of 214,107 students where 133,819 completed the next problem correctly. After subsetting the data to only include previous requesters, there are a total of 194,220 students where 121,148 completed the next problem correctly. As mentioned in the methodology, we subsetted the data with this variable to remove the cases of students who have never clicked on the button.

The odds ratio is aggregated over all experiments which tells us that the hints are 1.77% more effective in helping students get the next problem correct than explanations with a 95%

confidence interval from [0.9967; 1.0392]. After subsetting the data, hints are 2.28% more effective than explanations. Since the confidence interval is above 1.000, this means that we are 95% confident that being assigned to hints could have increased the odds of getting the next problem right by 0.04% to 4.57%. Since the p-value in the first row is above 0.05, then our claim is not significant (there is no strong evidence against the null hypothesis); however, in the second row, we have a p-value of 0.0462 which means that our claim is significant. Finally, both tau-squared are almost 0. This tells us that the effect did not differ between studies, hence causing little to no variability in student’s learning after using a hint versus an explanation.

RQ 2: Effect on Tutoring Observed

Results	Number of studies	Number of students observed	Number of students who requested tutoring	Odds Ratio with 95% confidence interval	P-Value	Tau^2
All students	101	214,107	38,453	1.0411 [0.9795; 1.1066]	0.1952	0.0023
Previous requesters	101	194,220	35,139	1.0414 [0.9772; 1.1097]	0.2114	0.001

The tutoring observed question determines if a student is more likely to click a hint button vs an explanation button by looking at 101 ASSISTments problems. There are a total of 214,107 students where 38,453 requested tutoring. After subsetting the data to only include previous requesters, there are a total of 194,220 students where 35,139 requested tutoring.

The odds ratio over all experiments of 1.0411 tells us that students assigned to hints are 4.11% more likely to request tutoring than students assigned to explanations with a 95% confidence interval of [0.9795; 1.1066]. After subsetting, students assigned hints are 4.14% more likely with [0.9772; 1.1097] as the confidence interval. The odds ratio is not statistically significant because the confidence interval for both the odds ratio go below and above 1.0. Additionally, the p-values of 0.1952 and 0.2114 are well above 0.05, making our claims not significant. Finally, the tau-squared of 0.0023 for all students tells us that there could be some difference between studies. The tau-squared of 0.001 tells us the effects may differ between studies as well, but with lower variability.

RQ 3: Effect on Next Problem Correctness (w/ Tutoring Observed subset)

<u>Results</u>	Number of studies	Number of students observed	Number of students with npc	Odds Ratio with 95% confidence interval	P-Value	Tau²
All students	100	38,453	12,332	1.0567 [0.9910; 1.1267]	0.0923	0.0195
Previous requesters	100	35,139	11,251	1.0622 [0.9945; 1.1430]	0.0713	0.0252

Our next set of research questions examine next problem correctness with more filters. This research question tells us if hints or explanations have an effect on students that have requested tutoring by looking at 100 ASSISTment problems. There are a total of 38,453 students who clicked on the tutoring button where 12,332 got the next problem correct. After subsetting

the data to only include previous requesters, there are a total of 35,139 students who requested tutoring where 11,251 got the next problem correct.

The odds ratio over all experiments of 1.0567 tells us that hints are 5.67% more effective than explanations with a confidence interval between [0.9910; 1.1267]. After subsetting, hints are 6.22% more effective than explanations with [0.9945; 1.1430] as the confidence interval. Again, the odds ratio is not clinically significant because the confidence interval for both the odds ratio go below and above 1.0. Additionally, the p-values of 0.0923 and 0.0713 are above 0.05, making our claims not significant. Finally, the tau squared of 0.0195 and 0.0252 tells us that there is some difference in the effect of the studies. Do note that this is the question where we used tutoring_observed as a subset of students who all clicked on the button. As mentioned in the methodology, this can lead to biased results. This means that we cannot make any claims regarding the likeness of hints or explanations having an effect on next problem correctness.

RQ 4: Effect on Problem Completed

<u>Results</u>	Number of studies	Number of students observed	Number of students who completed the problem	Odds Ratio with 95% confidence interval	P-Value	Tau²
All students	101	214,107	208,560	0.9390 [0.8318; 1.0599]	0.3082	0.0174
Previous requesters	101	194,220	189,173	0.9299 [0.8157; 1.0601]	0.2771	0.0165

This research question finds out the effect of hints and explanations on students who actually put the answer in the text box by looking at 101 ASSISTment problems. The odds ratio over all experiments of 0.9390 for all students who answered their problem tells us that explanations are 6.1% more effective than hints with the 95% confidence interval being [0.8318; 1.0599]. After subsetting the data to only include previous requesters, explanations are 7.01% more effective than hints with the confidence interval being [0.8157; 1.0601]. Additionally, the p-values of 0.3082 and 0.2771 shows that our claim is not significant. Both the tau-squared are far enough from 0 to imply that the effects could differ between studies.

RQ 5: Effect on Try Next

<u>Results</u>	Number of studies	Number of students observed	Number of students who tried the next problem	Odds Ratio with 95% confidence interval	P-Value	Tau²
All students	101	214,107	204,931	0.9717 [0.8992; 1.0502]	0.4694	0.0063
Previous requesters	101	194,220	185,894	0.9466 [0.8737; 1.0256]	0.1794	0.0044

The Effect on Try Next question looks into 101 ASSISTments problems examining whether hints or explanations have an effect on students who complete the next problem and click the student support button. When including all students, the odds ratio tells us that explanations caused an increase of 2.83% in the likelihood of a student requesting tutoring on the

next problem with a 95% confidence interval of [0.8992; 1.0502]. After subsetting the data to include only previous requesters, explanations are 5.34% more effective than hints with the confidence interval being [0.8737; 1.0256]. The p-values of 0.4694 and 0.1794 show that our claim is not significant. Both the tau-squared are slightly above 0 which shows that the effects may differ between studies.

RQ 6: Effect on Assignment Completed

<u>Results</u>	Number of studies	Number of students observed	Number of students who completed the assignment	Odds Ratio with 95% confidence interval	P-Value	Tau²
All students	101	214,107	192,544	1.0291 [0.9908; 1.0689]	0.1385	< 0.0001
Previous requesters	101	194,220	174,724	1.0180 [0.9778; 1.0600]	0.3852	0.0011

The Effect on Assignment Completed Question examines 101 ASSISTments problems on whether hints or explanations have an effect on students who completed the entire assignment. When including all the students, the odds ratio tells us that hints are 2.91% more effective compared to explanations with a confidence interval of [0.9908; 1.0689]. After subsetting by previous requesters, hints are 1.8% more effective than explanations with a confidence interval of [0.9778; 1.0600]. The p-values for all students and only previous requesters are both above

.05, therefore our claim is not significant. The tau-squared values of < 0.0001 and 0.0011 are close to zero, so there must have been little difference between the effects on each study.

RQ 7: Effect on Answer Given

Results	Number of studies	Number of students observed	Number of students given the answer	Odds Ratio with 95% confidence interval	P-Value	Tau²
All students	101	214,107	33,408	0.2951 [0.2500; 0.3484]	< 0.0001	0.0733
Previous requesters	101	194,220	30,559	0.3025 [0.2561; 0.3573]	< 0.0001	0.0733

The Effect on Answer Given question examines 101 ASSISTments problems on whether hints or explanations have an effect on the students who received the answer for their problem. When including all the students, the odds ratio of 0.2951 tells us that students assigned to explanations have a 70.49% likelihood of seeing the answer compared to hints with a confidence interval of [0.2500; 0.3484]. After subsetting to include only previous requesters, the odds ratio is very similar with explanations having a 69.75% likelihood compared to hints with a confidence interval of [0.2561; 0.3573]. Both the p-values were really close to 0 which implies that our claim is significant. The tau-squared values of 0.0733 are relatively high meaning the effects are likely to be different between each study. This makes sense as part of the effect is students may be more likely to stop going through the hints to get some partial credit on the problem as mentioned in the overview.

Chapter 5: Conclusion

Based on the data analysis above, we were able to determine that there may not be a difference between hints versus explanations on a student's learning in ASSISTments. Even after comparing the results between all students and previous requesters, there is little to no significant difference between the two categories. We also found a pattern where the number of students who requested tutoring were less than twenty percent of the number of students observed. Additionally, we also found no substantial evidence in the rest of our research questions due to the odds ratio and the confidence intervals being closer to 1.0 and the p-values being well above 0.05 with a variability in the number in the difference between the number of students observed and the number of students incorporating a certain variable. If we round up the odds ratio from our results, then there is basically no effect because the odds go up by at most 4% in question two. This may increase the chance of students choosing hints over explanations, however not many people requested the tutoring. The results of the statistical analysis were done using different research questions, however, we did not find any significant evidence to prove if hints or explanations are better for students when solving a problem. Instead of “fishing for significance” by running additional analyses, we came up with the following recommendations to raise new questions for the future.

However, throughout the duration of the work, our team was successfully able to conduct analysis on all our research questions which were defined at the initiation of the project. We also learned how to conduct meta-analysis in R through effect-size, pooling effect-size, and meta-regression to conduct statistical analysis on the Methods of Learning that work in Educational Technology like ASSISTments.

Chapter 6: Recommendations

Based on the results and conclusion of the project, we have a few recommendations for future researchers to explore related to ASSISTments' effectiveness of student's learning:

- Take into consideration if different high school grades choose different student supports when stuck on a problem. Is it possible that higher grades are more likely to choose explanations to help their understanding rather than hints? This can further help understand the effectiveness of hints versus explanations.
- Further research to find if there are features of the student supports that predict when one is more effective than the other. Consider looking at the following variables and comparing the results
 - *Student_support_text_length* : This variable looks at the character count of the text of the student support. Analyze if the length of the student support has any impact on student's learning.
 - *Student_support_contains_video* : This indicates if the student support contains a link to a video to help the student in a problem. If a student clicks watched the linked video, does that help the student answer the next question? This can tell us if videos are more effective than the student support that contains only text.
 - *Student_support_contains_image* : This means that the student support contains an image to further help the understanding of the student. This variable can be important to analyze since it can be calculated if the image has more effect on a student's learning compared to the text or video.

- *student_support_contains_link* : This indicates that the student support contains a link to an external site which is not a video link. This variable can answer if an external site has an impact on the student's next problem correctness.
- The dataset had no mention of the student's other characteristics like state test scores and GPA. All these factors could also influence which student support is more effective for certain students. By creating different categories of students based on these characteristics and comparing the data to the student support they find more effective, there could be an analysis on which student support works best for what kind of students. Maybe answering if students with higher GPAs find hints more effective than explanations.
- The students in this dataset were selected to either receive a hint or an explanation, at random, from a math class. It would be helpful to analyze results from a different subject (like science), to see if the results are similar to the ones mentioned in this paper. Different student supports might work better for different high school courses. For example, it could be beneficial for the students in the science class to use explanations instead of hints when solving a problem. Each course has different content, hence, analyzing the effects of between hints versus explanations for a science class will broaden the scope of this project.
- Looking further at how the average effect size differs depending on who wrote the student support. Do teachers play a role in the effectiveness on student's learning on ASSISTments? This can be done by comparing datasets from different teachers' math classes to another and analyzing the effect size and odds ratio for each class. Maybe one

teacher's hints have more effect on the next problem compared to another teacher. This can also influence which student support is more helpful for students.

- Since the Student Support Gathered is between 2018-2021, analyze if COVID-19 had a drastic impact on students learning through student support. Since the students were learning the material remotely during that time, does that have any influence on the student support's effects. It would be helpful to separate each year's data and then find results on the research questions to see the difference every year.
- As more data becomes available (after 2021), re-evaluate the research questions from this project and update the results. It is essential to keep the results updated. Hence, as there is more data, it would be helpful to compare the newer results to the ones mentioned in this paper.

Appendix 1

<p>Student_support_logs</p>	<p>This table contains one entry for each instance of the SSDS randomly choosing between multiple student supports, including the option to not receive a student support.</p>
<p>no_next problem</p>	<p>The dependent measure used in these experiments is “next problem correctness”, which is determined by the score the student received on the next graded problem they answered within the same assignment they received a student support within. If this flag is set to 1, it indicates that there was no opportunity for the student to answer a graded problem following the problem they received a student support on before the end of their assignment. If the student did not complete their assignment, this flag will be 0 because there may have been the opportunity to complete a graded problem.</p>
<p>student_support_log_id</p>	<p>This is the student support log id. Each database should not have duplicate IDs. However, as discussed above this is not the case. This column can be used to identify groups of ambiguous logs.</p>
<p>Teacher_id</p>	<p>The ID of the teacher of the class the student was doing work for when they were provided the selected student support. This ID is the same type of ID as the user_id in this table, and the content_creator_id in student_support_features.csv. Therefore, one can use these teacher IDs to remove cases when teachers were testing material for their</p>

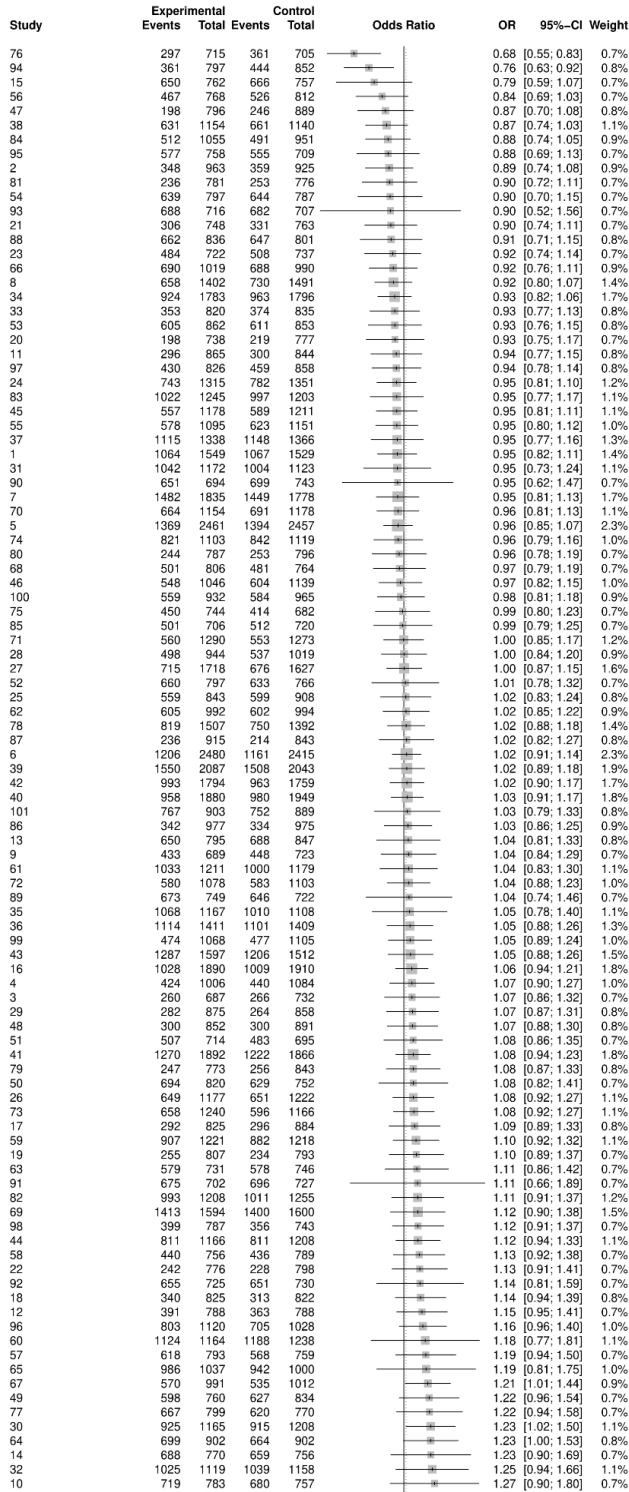
	<p>class and identify when students were randomly assigned content created by their teacher. In ASSISTments 1.0, users were able to completely remove information on their assignments when they deleted them. Therefore, some values are missing because they are linked to deleted assignments.</p>
sequence_id	<p>The ID of the sequence that contained the problem that the selected student support was provided for. A sequence is a series of problems, usually a sequence contains a small set of problems on the same subject. In ASSISTments 1.0, users were able to completely remove information on their assignments when they deleted them. Therefore, some values are missing because they are linked to deleted assignments.</p>
Assignment_id	<p>This column provides the assignment ID for the assignment the student was completing in which they were provided the selected student support. An assignment is a sequence that has been assigned to one particular class with a particular release date, and therefore it gets a unique ID separate from other instances of the same sequence being assigned to other classes, or the same class at other times.</p>
User_id	<p>This column provides the user ID for the student that had the opportunity to observe the provided student support.</p>
problem_id	<p>This column provides the problem ID for the problem that the selected student support was provided for.</p>
next_problem_id	<p>This column provides the problem ID for the</p>

	<p>next graded problem within the same assignment after the student was provided with student support. This column may be missing if there was no graded problem completed by the student following the problem in which a student support was provided.</p>
randomized_between_student_supports	<p>This flag indicates that the student was randomized between receiving multiple possible student supports.</p>
selected_student_support_id	<p>This column provides the ID of the student support selected by the SSDS, which was made available to the student. If the student was randomized between a student support and receiving the answer with no tutoring, then when the student received no tutoring, this column will be 0.</p>
alternative_student_support_id?	<p>These four columns provide the IDs of the other student supports that the SSDS could have selected when randomly selecting a student support. When the student was randomized between being provided with a student support or just the answer with no tutoring, an ID of 0 indicates the condition in which the student was provided with just the answer.</p>
Tutoring_observed	<p>This flag indicates that the student observed a student support or, when the student was given just the answer, that they observed the answer.</p>
Answer_given	<p>This flag indicates that a student was provided with the answer. If the student support provided to the student was an explanation, or</p>

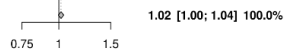
	<p>the student was only given the answer, then this flag and the previous flag will be identical. However, if the student support provided to the student was a hint, then when the student observed some of the hints, but not the final hint, which provides the answer, this flag will be 0 while the previous flag is 1.</p>
<p>problem_completed</p>	<p>This flag indicates that the student completed the problem that the selected student support was provided for.</p>
<p>Next_problem_correctness</p>	<p>This flag indicates that the student got the next graded problem in their assignment correct on their first try with no tutoring. This value can be missing if the student never attempted to answer a next problem, or there were no graded problems following the problem in which they were provided the selected student support.</p>

Appendix 2: Forest Plots

Next Problem Correctness (All Students)



Random effects model
Heterogeneity: $I^2 = 1\%$, $p = 0.45$



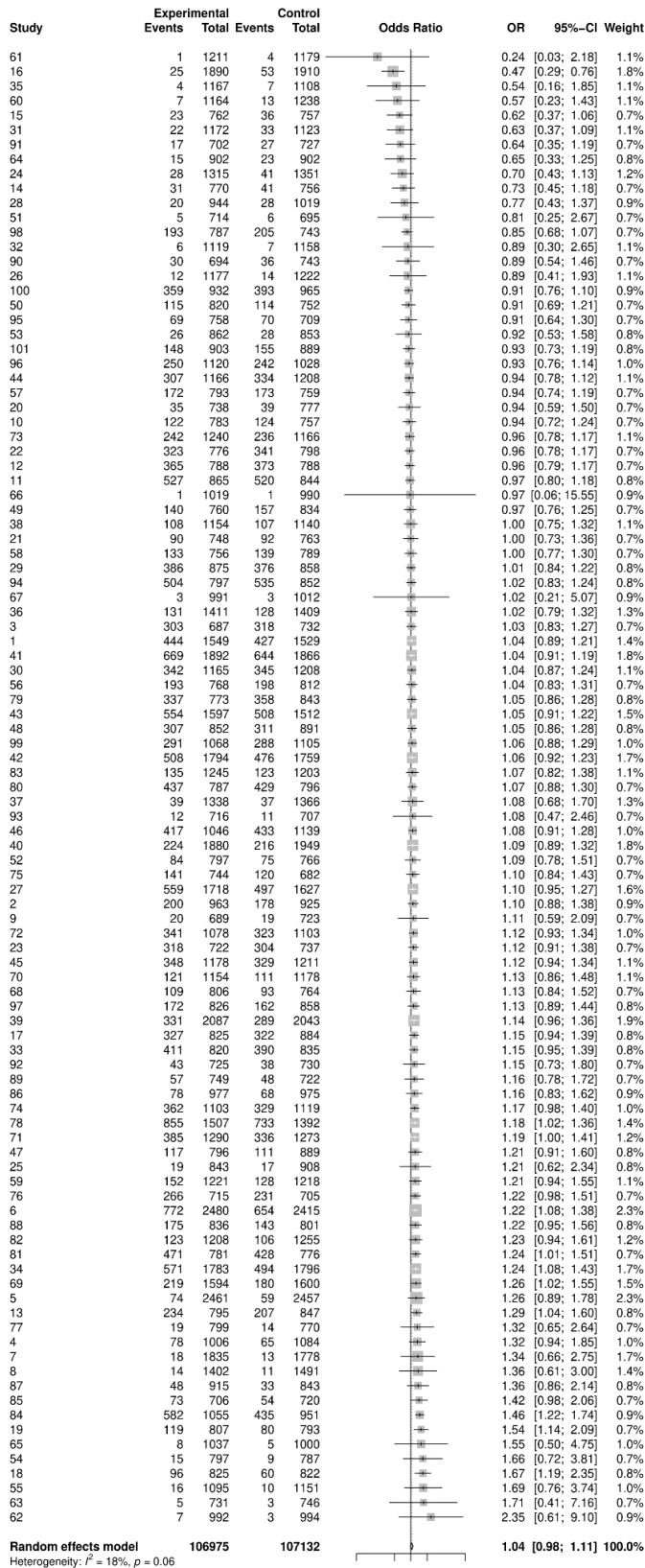
Next Problem Correctness (All Previous Requesters)

Study	Experimental		Control		Odds Ratio	OR	95%-CI	Weight
	Events	Total	Events	Total				
76	265	638	332	648		0.68	[0.54; 0.84]	0.7%
94	323	725	406	767		0.71	[0.58; 0.88]	0.8%
56	417	690	478	734		0.82	[0.66; 1.01]	0.7%
47	176	737	223	813		0.83	[0.66; 1.04]	0.8%
15	610	714	604	691		0.84	[0.62; 1.15]	0.7%
38	577	1054	606	1031		0.85	[0.71; 1.01]	1.1%
88	586	748	593	736		0.87	[0.68; 1.12]	0.8%
84	465	953	468	900		0.88	[0.73; 1.06]	1.0%
8	588	1274	676	1371		0.88	[0.76; 1.03]	1.4%
2	320	884	332	853		0.89	[0.73; 1.08]	0.9%
90	584	625	631	671		0.90	[0.58; 1.42]	0.7%
34	628	1592	876	1612		0.91	[0.79; 1.05]	1.7%
37	1009	1214	1049	1244		0.91	[0.74; 1.13]	1.3%
95	534	698	503	645		0.92	[0.77; 1.19]	0.7%
66	615	919	612	891		0.92	[0.76; 1.12]	0.9%
21	278	675	304	706		0.93	[0.75; 1.15]	0.7%
46	496	960	552	1034		0.93	[0.78; 1.11]	1.0%
80	217	712	229	719		0.94	[0.75; 1.17]	0.7%
7	1355	1683	1330	1632		0.94	[0.79; 1.12]	1.7%
55	526	992	564	1033		0.94	[0.79; 1.12]	1.0%
33	317	741	335	756		0.94	[0.77; 1.15]	0.8%
81	219	711	225	701		0.94	[0.75; 1.18]	0.7%
1	960	1399	984	1408		0.94	[0.80; 1.11]	1.4%
74	746	1009	782	1042		0.94	[0.77; 1.15]	1.1%
23	444	666	457	673		0.95	[0.75; 1.19]	0.7%
54	567	705	573	705		0.95	[0.73; 1.23]	0.7%
24	683	1207	717	1238		0.95	[0.81; 1.11]	1.3%
70	605	1064	631	1086		0.95	[0.80; 1.13]	1.1%
97	391	750	417	782		0.95	[0.78; 1.17]	0.8%
45	501	1075	529	1108		0.96	[0.81; 1.13]	1.1%
11	269	795	265	765		0.96	[0.78; 1.19]	0.8%
5	1250	2234	1273	2240		0.96	[0.86; 1.09]	2.3%
31	949	1070	893	1003		0.97	[0.73; 1.27]	1.1%
20	182	675	195	710		0.97	[0.77; 1.24]	0.7%
61	447	853	492	929		0.98	[0.81; 1.18]	0.9%
28	924	1088	898	1054		0.98	[0.77; 1.24]	1.1%
75	409	675	387	634		0.98	[0.79; 1.23]	0.7%
93	627	650	610	632		0.98	[0.54; 1.78]	0.7%
9	388	620	412	656		0.99	[0.79; 1.24]	0.7%
83	930	1127	885	1071		0.99	[0.80; 1.24]	1.1%
53	538	764	537	761		0.99	[0.80; 1.24]	0.8%
68	463	734	438	693		0.99	[0.80; 1.23]	0.7%
100	505	841	522	868		1.00	[0.82; 1.21]	0.9%
62	548	897	539	883		1.00	[0.83; 1.21]	0.9%
13	597	733	629	773		1.00	[0.78; 1.30]	0.8%
27	649	1544	611	1460		1.01	[0.87; 1.16]	1.5%
72	533	990	540	1010		1.02	[0.85; 1.21]	1.0%
78	740	1370	674	1261		1.02	[0.88; 1.19]	1.4%
71	523	1191	504	1163		1.02	[0.87; 1.20]	1.2%
17	256	749	267	795		1.03	[0.83; 1.27]	0.8%
92	589	655	588	656		1.03	[0.72; 1.48]	0.7%
42	906	1630	868	1584		1.03	[0.90; 1.19]	1.7%
39	1405	1887	1359	1845		1.04	[0.90; 1.21]	1.9%
86	307	872	304	889		1.05	[0.86; 1.27]	0.9%
3	236	625	247	673		1.05	[0.84; 1.31]	0.7%
6	1107	2266	1044	2188		1.05	[0.93; 1.18]	2.3%
40	857	1695	871	1763		1.05	[0.92; 1.20]	1.8%
4	376	894	403	986		1.05	[0.87; 1.26]	1.0%
85	450	632	445	634		1.05	[0.82; 1.34]	0.7%
87	216	825	192	761		1.05	[0.84; 1.32]	0.8%
25	502	755	532	814		1.05	[0.85; 1.30]	0.8%
52	597	721	566	690		1.05	[0.80; 1.39]	0.7%
51	452	639	439	631		1.06	[0.83; 1.34]	0.7%
69	1279	1449	1283	1464		1.06	[0.85; 1.33]	1.5%
99	425	958	430	1003		1.06	[0.89; 1.27]	1.0%
26	588	1058	601	1112		1.06	[0.90; 1.26]	1.1%
41	1140	1709	1098	1685		1.07	[0.93; 1.23]	1.7%
29	253	785	238	776		1.08	[0.87; 1.33]	0.8%
43	1167	1454	1062	1343		1.08	[0.89; 1.29]	1.4%
16	933	1720	909	1735		1.08	[0.94; 1.23]	1.8%
50	627	741	566	678		1.09	[0.82; 1.45]	0.7%
59	825	1113	795	1098		1.09	[0.90; 1.32]	1.1%
73	598	1127	553	1088		1.09	[0.93; 1.29]	1.1%
36	1012	1272	1003	1286		1.10	[0.91; 1.33]	1.3%
58	393	684	392	711		1.10	[0.89; 1.36]	0.7%
101	703	826	680	812		1.11	[0.85; 1.45]	0.8%
89	609	675	582	652		1.11	[0.78; 1.58]	0.7%
48	272	774	265	809		1.11	[0.90; 1.37]	0.8%
63	525	659	521	671		1.13	[0.87; 1.47]	0.7%
19	234	735	211	722		1.13	[0.90; 1.41]	0.8%
35	964	1053	908	1003		1.13	[0.84; 1.53]	1.1%
82	901	1091	903	1119		1.13	[0.91; 1.41]	1.1%
79	222	690	227	772		1.14	[0.91; 1.42]	0.8%
44	745	1074	723	1088		1.14	[0.95; 1.37]	1.1%
22	213	698	200	722		1.15	[0.91; 1.44]	0.7%
98	365	721	314	667		1.15	[0.93; 1.42]	0.7%
96	731	1023	639	938		1.17	[0.97; 1.42]	1.0%
32	925	1012	942	1046		1.17	[0.87; 1.58]	1.1%
57	553	714	512	687		1.17	[0.92; 1.50]	0.7%
18	313	753	281	746		1.18	[0.96; 1.45]	0.8%
12	358	723	328	724		1.18	[0.96; 1.46]	0.7%
64	626	815	607	825		1.19	[0.95; 1.49]	0.8%
49	539	688	565	752		1.20	[0.94; 1.53]	0.7%
67	509	898	473	908		1.20	[1.00; 1.45]	0.9%
14	640	716	608	695		1.20	[0.87; 1.67]	0.7%
65	892	928	852	906		1.22	[0.81; 1.82]	0.9%
10	658	717	626	695		1.23	[0.85; 1.77]	0.7%
30	832	1046	831	1096		1.24	[1.01; 1.52]	1.1%
77	616	735	561	696		1.25	[0.95; 1.63]	0.7%
91	606	628	631	660		1.27	[0.72; 2.23]	0.7%
60	1002	1036	1069	1117		1.32	[0.85; 2.07]	1.1%

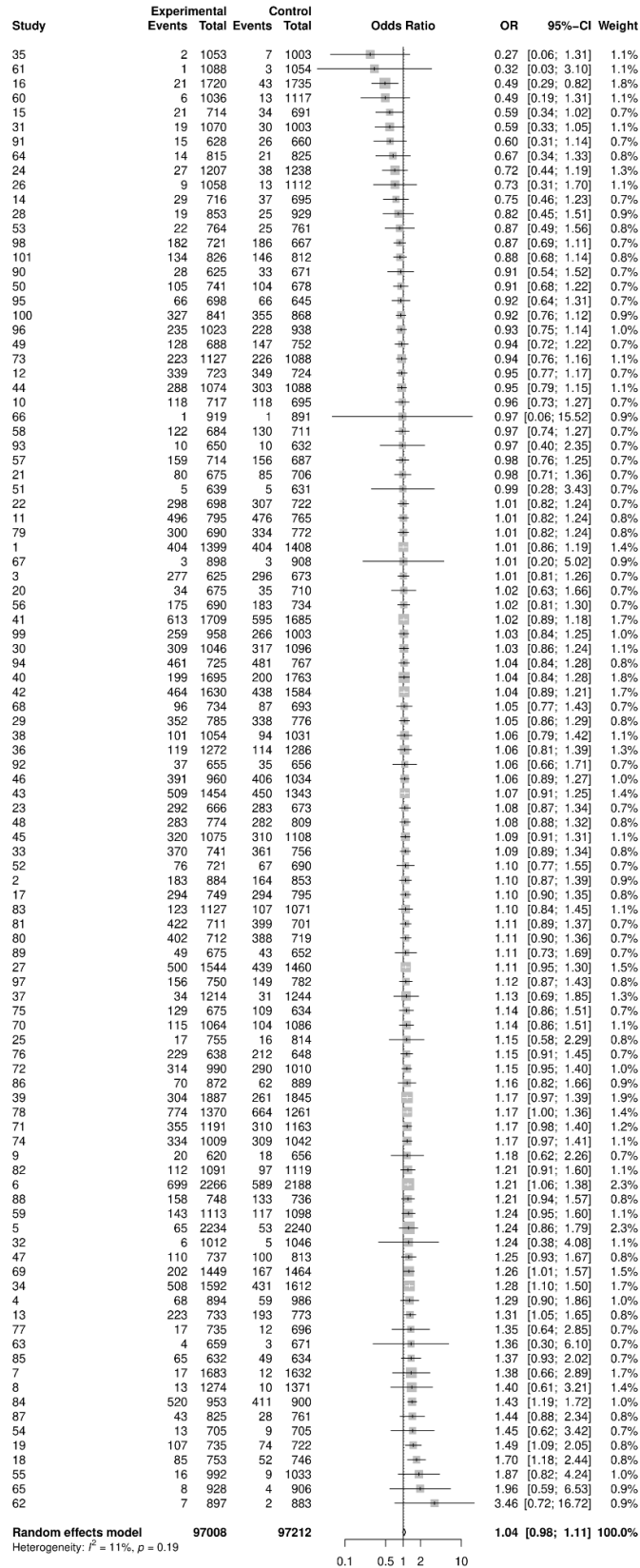
Random effects model 97008 97212 1.02 [1.00; 1.05] 100.0%
 Heterogeneity: $I^2 = 3\%$, $p = 0.38$



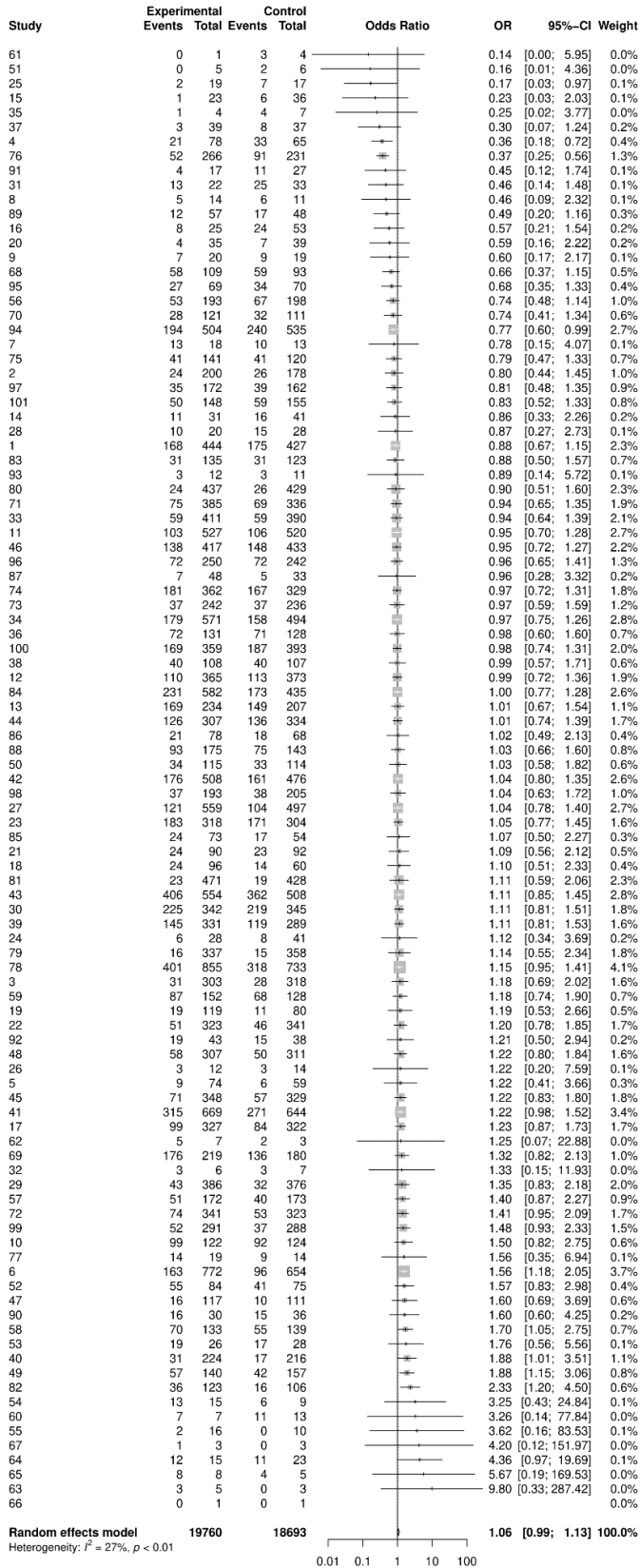
Tutoring Observed (All Students)



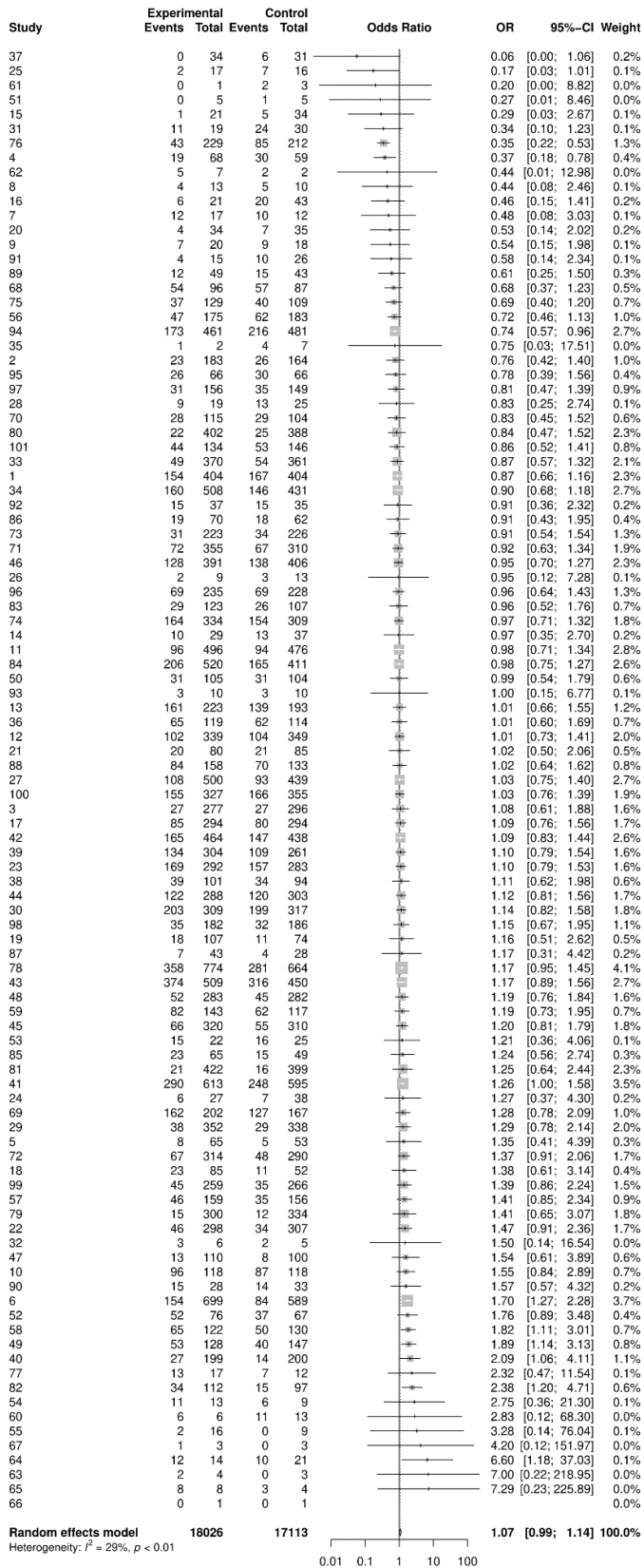
Tutoring Observed (All Previous Requesters)



Next Problem Correctness Subsetted by Tutoring Observed (All Students)



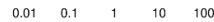
Next Problem Correctness Subsetted by Tutoring Observed (All Previous Requesters)



Problem Completed (All Students)

Study	Experimental Events	Experimental Total	Control Events	Control Total	Odds Ratio	OR	95%-CI	Weight
64	900	902	902	902		0.20	[0.01; 4.16]	0.8%
15	760	762	757	757		0.20	[0.01; 4.19]	0.7%
93	714	716	707	707		0.20	[0.01; 4.21]	0.7%
66	1017	1019	990	990		0.21	[0.01; 4.28]	0.9%
5	2445	2461	2453	2457		0.25	[0.08; 0.75]	2.3%
62	991	992	994	994		0.33	[0.01; 8.17]	0.9%
51	713	714	695	695		0.34	[0.01; 8.41]	0.7%
35	1164	1167	1107	1108		0.35	[0.04; 3.37]	1.1%
83	1234	1245	1199	1203		0.37	[0.12; 1.18]	1.1%
55	1083	1095	1146	1151		0.39	[0.14; 1.12]	1.0%
96	1102	1120	1020	1028		0.48	[0.21; 1.11]	1.0%
32	1117	1119	1157	1158		0.48	[0.04; 5.33]	1.1%
56	750	768	802	812		0.52	[0.24; 1.13]	0.7%
95	754	758	707	709		0.53	[0.10; 2.92]	0.7%
33	796	820	821	835		0.57	[0.29; 1.10]	0.8%
34	1708	1783	1749	1796		0.61	[0.42; 0.89]	1.7%
41	1833	1892	1828	1866		0.65	[0.43; 0.98]	1.8%
65	1020	1037	989	1000		0.67	[0.31; 1.43]	1.0%
22	742	776	774	798		0.68	[0.40; 1.15]	0.7%
61	1208	1211	1177	1179		0.68	[0.11; 4.10]	1.1%
31	1163	1172	1117	1123		0.69	[0.25; 1.96]	1.1%
8	1394	1402	1485	1491		0.70	[0.24; 2.03]	1.4%
50	814	820	748	752		0.73	[0.20; 2.58]	0.7%
23	692	722	714	737		0.74	[0.43; 1.29]	0.7%
26	1168	1177	1215	1222		0.75	[0.28; 2.01]	1.1%
6	2431	2480	2379	2415		0.75	[0.49; 1.16]	2.3%
49	748	760	824	834		0.76	[0.32; 1.76]	0.7%
14	766	770	753	756		0.76	[0.17; 3.42]	0.7%
44	1151	1166	1196	1208		0.77	[0.36; 1.65]	1.1%
94	767	797	827	852		0.77	[0.45; 1.33]	0.8%
78	1307	1507	1243	1392		0.78	[0.62; 0.98]	1.4%
3	668	687	716	732		0.79	[0.40; 1.54]	0.7%
88	757	836	739	801		0.80	[0.57; 1.14]	0.8%
60	1157	1164	1232	1238		0.80	[0.27; 2.40]	1.1%
28	935	944	1011	1019		0.82	[0.32; 2.14]	0.9%
29	832	875	823	858		0.82	[0.52; 1.30]	0.8%
18	802	825	803	822		0.83	[0.45; 1.53]	0.8%
36	1403	1411	1402	1409		0.88	[0.32; 2.42]	1.3%
70	1090	1154	1120	1178		0.88	[0.61; 1.27]	1.1%
75	683	744	632	682		0.89	[0.60; 1.31]	0.7%
27	1678	1718	1592	1627		0.92	[0.58; 1.46]	1.6%
39	1931	2087	1901	2043		0.92	[0.73; 1.17]	1.9%
76	625	715	622	705		0.93	[0.67; 1.27]	0.7%
40	1852	1880	1922	1949		0.93	[0.55; 1.58]	1.8%
43	1527	1597	1450	1512		0.93	[0.66; 1.32]	1.5%
90	690	694	739	743		0.93	[0.23; 3.75]	0.7%
58	755	756	788	789		0.96	[0.06; 15.35]	0.7%
98	764	787	722	743		0.97	[0.53; 1.76]	0.7%
47	759	796	849	889		0.97	[0.61; 1.53]	0.8%
72	1030	1078	1055	1103		0.98	[0.65; 1.47]	1.0%
79	758	773	827	843		0.98	[0.48; 1.99]	0.8%
85	700	706	714	720		0.98	[0.31; 3.05]	0.7%
92	717	725	722	730		0.99	[0.37; 2.66]	0.7%
97	756	826	785	858		1.00	[0.71; 1.41]	0.8%
54	790	797	780	787		1.01	[0.35; 2.90]	0.7%
71	1145	1290	1128	1273		1.02	[0.79; 1.30]	1.2%
101	895	903	881	889		1.02	[0.38; 2.72]	0.8%
86	946	977	943	975		1.04	[0.63; 1.71]	0.9%
2	950	963	912	925		1.04	[0.48; 2.26]	0.9%
30	1129	1165	1169	1208		1.05	[0.66; 1.66]	1.1%
69	1534	1594	1537	1600		1.05	[0.73; 1.50]	1.5%
12	772	788	771	788		1.06	[0.53; 2.12]	0.7%
80	774	787	782	796		1.07	[0.50; 2.28]	0.7%
84	872	1055	777	951		1.07	[0.85; 1.34]	0.9%
48	826	852	862	891		1.07	[0.62; 1.83]	0.8%
87	899	915	827	843		1.09	[0.54; 2.19]	0.8%
73	1149	1240	1073	1166		1.09	[0.81; 1.48]	1.1%
45	1150	1178	1179	1211		1.11	[0.67; 1.86]	1.1%
11	829	865	805	844		1.12	[0.70; 1.77]	0.8%
59	1200	1221	1194	1218		1.15	[0.64; 2.07]	1.1%
24	1295	1315	1327	1351		1.17	[0.64; 2.13]	1.2%
21	743	748	757	763		1.18	[0.36; 3.88]	0.7%
16	1847	1890	1858	1910		1.20	[0.80; 1.81]	1.8%
1	1487	1549	1456	1529		1.20	[0.85; 1.70]	1.4%
7	732	825	765	884		1.22	[0.92; 1.64]	0.8%
81	768	781	780	776		1.24	[0.59; 2.60]	0.7%
9	686	689	719	723		1.27	[0.28; 5.70]	0.7%
53	835	862	819	853		1.28	[0.77; 2.15]	0.8%
20	733	738	770	777		1.33	[0.42; 4.22]	0.7%
77	792	799	761	770		1.34	[0.50; 3.61]	0.7%
82	1202	1208	1246	1255		1.45	[0.51; 4.08]	1.2%
67	989	991	1009	1012		1.47	[0.25; 8.82]	0.9%
74	1057	1103	1051	1119		1.49	[1.01; 2.18]	1.0%
42	1753	1794	1699	1759		1.51	[1.01; 2.26]	1.7%
52	795	797	763	766		1.56	[0.26; 9.38]	0.7%
68	800	806	755	764		1.59	[0.56; 4.49]	0.7%
10	779	783	750	757		1.82	[0.53; 6.23]	0.7%
4	993	1006	1058	1084		1.88	[0.96; 3.67]	1.0%
19	801	807	782	793		1.88	[0.69; 5.10]	0.7%
99	1029	1068	1030	1105		1.92	[1.29; 2.86]	1.0%
13	786	795	828	847		2.00	[0.90; 4.46]	0.8%
7	1833	1835	1774	1778		2.07	[0.38; 11.30]	1.7%
57	791	793	755	759		2.10	[0.38; 11.47]	0.7%
25	840	843	901	908		2.18	[0.56; 8.44]	0.8%
89	744	749	711	722		2.30	[0.80; 6.66]	0.7%
46	1039	1046	1117	1139		2.92	[1.24; 6.87]	1.0%
37	1337	1338	1363	1366		2.94	[0.31; 28.33]	1.3%
38	1153	1154	1137	1140		3.04	[0.32; 29.29]	1.1%
100	925	932	939	965		3.66	[1.58; 8.47]	0.9%
91	701	702	723	727		3.88	[0.43; 34.78]	0.7%
63	730	731	740	746		5.92	[0.71; 49.29]	0.7%

Random effects model
Heterogeneity: $I^2 = 17\%$, $p = 0.08$



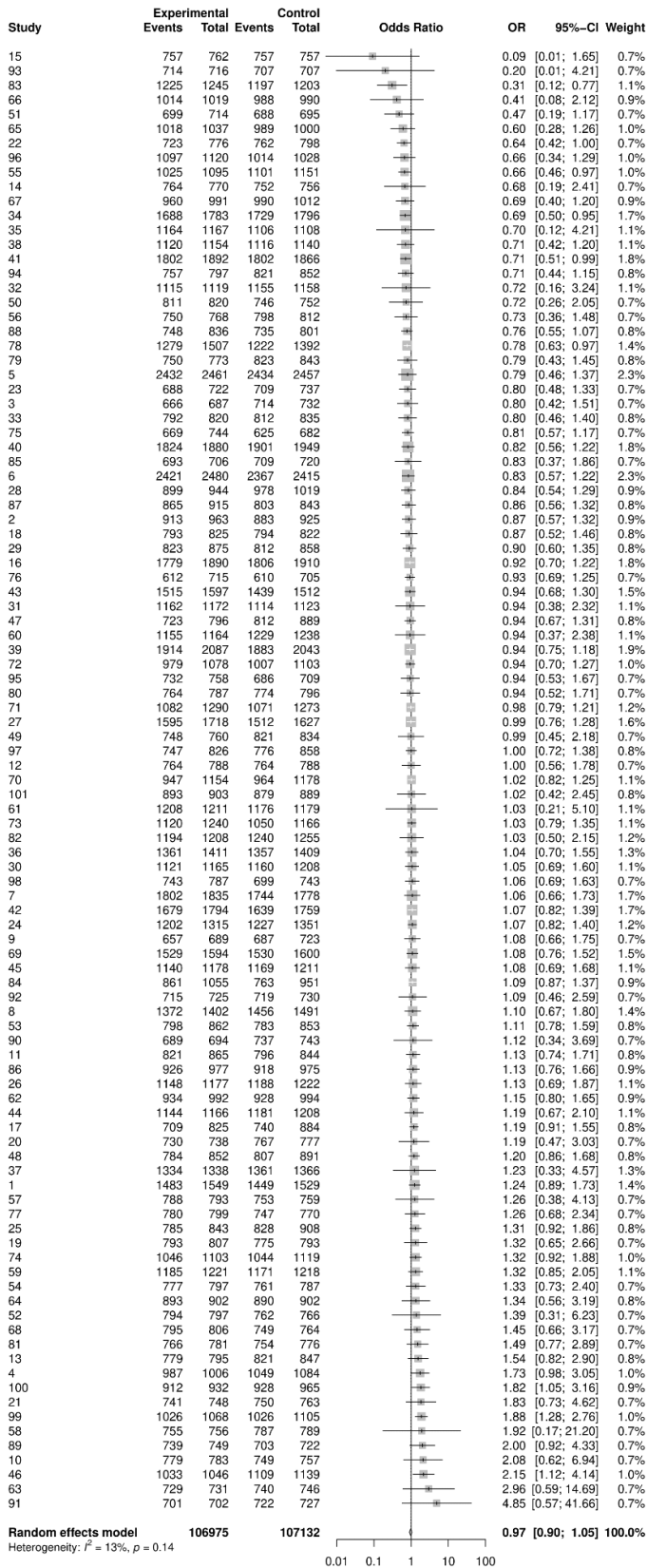
Problem Completed (All Previous Requesters)

Study	Experimental Events	Experimental Total	Control Total	Odds Ratio	OR	95%—CI	Weight
32	1010	1012	1046	1046	0.19	[0.01; 4.03]	1.1%
93	648	650	632	632	0.21	[0.01; 4.28]	0.7%
66	917	919	891	891	0.21	[0.01; 4.29]	0.9%
15	712	714	691	691	0.21	[0.01; 4.30]	0.7%
5	2220	2234	2237	2240	0.21	[0.06; 0.74]	2.3%
64	814	815	825	825	0.33	[0.01; 8.09]	0.8%
51	638	639	631	631	0.34	[0.01; 8.29]	0.7%
62	896	897	883	883	0.34	[0.01; 8.31]	0.9%
35	1050	1053	1002	1003	0.35	[0.04; 3.36]	1.1%
56	674	690	727	734	0.41	[0.17; 0.99]	0.7%
83	1117	1127	1067	1071	0.42	[0.13; 1.34]	1.1%
96	1006	1023	930	938	0.51	[0.22; 1.19]	1.0%
14	712	716	693	695	0.51	[0.09; 2.81]	0.7%
33	719	741	744	756	0.53	[0.26; 1.07]	0.8%
55	983	992	1028	1033	0.53	[0.18; 1.59]	1.0%
36	1265	1272	1282	1286	0.56	[0.16; 1.93]	1.3%
31	1061	1070	998	1003	0.59	[0.20; 1.77]	1.1%
34	1525	1592	1571	1612	0.59	[0.40; 0.88]	1.7%
44	1060	1074	1079	1088	0.63	[0.27; 1.47]	1.1%
41	1657	1709	1652	1685	0.64	[0.41; 0.99]	1.7%
23	636	666	653	673	0.65	[0.36; 1.16]	0.7%
3	607	625	660	673	0.66	[0.32; 1.37]	0.7%
49	676	688	743	752	0.68	[0.29; 1.63]	0.7%
61	1085	1088	1052	1054	0.69	[0.11; 4.12]	1.1%
6	2222	2266	2158	2188	0.70	[0.44; 1.12]	2.3%
26	1050	1058	1106	1112	0.71	[0.25; 2.06]	1.1%
95	695	698	643	645	0.72	[0.12; 4.33]	0.7%
22	669	698	700	722	0.73	[0.41; 1.27]	0.7%
65	914	928	896	906	0.73	[0.32; 1.65]	0.9%
88	670	748	678	736	0.73	[0.51; 1.05]	0.8%
94	697	725	744	767	0.77	[0.44; 1.35]	0.8%
8	1268	1274	1366	1371	0.77	[0.24; 2.54]	1.4%
78	1183	1370	1122	1261	0.78	[0.52; 0.99]	1.4%
80	701	712	710	719	0.81	[0.33; 1.96]	0.7%
70	1004	1064	1034	1086	0.84	[0.57; 1.23]	1.1%
40	1668	1695	1739	1763	0.85	[0.49; 1.48]	1.8%
54	698	705	699	705	0.86	[0.29; 2.56]	0.7%
18	732	753	728	746	0.86	[0.46; 1.63]	0.8%
50	736	741	674	678	0.87	[0.23; 3.27]	0.7%
101	818	826	805	812	0.89	[0.32; 2.46]	0.8%
43	1387	1454	1287	1343	0.90	[0.63; 1.29]	1.4%
69	1389	1449	1409	1464	0.90	[0.62; 1.31]	1.5%
75	619	675	586	634	0.91	[0.61; 1.35]	0.7%
28	845	853	921	929	0.92	[0.34; 2.46]	0.9%
60	1030	1036	1111	1117	0.93	[0.30; 2.88]	1.1%
76	555	638	569	648	0.93	[0.67; 1.29]	0.7%
47	701	737	776	813	0.93	[0.58; 1.49]	0.8%
12	708	723	710	724	0.93	[0.45; 1.94]	0.7%
90	621	625	667	671	0.93	[0.23; 3.74]	0.7%
81	698	711	689	701	0.94	[0.42; 2.06]	0.7%
39	1747	1887	1714	1845	0.95	[0.74; 1.22]	1.9%
97	683	750	715	782	0.96	[0.67; 1.36]	0.8%
79	676	690	757	772	0.96	[0.46; 2.00]	0.8%
58	683	684	710	711	0.96	[0.06; 15.41]	0.7%
48	749	774	783	809	0.99	[0.57; 1.74]	0.8%
85	626	632	628	634	1.00	[0.32; 3.11]	0.7%
92	648	655	649	656	1.00	[0.35; 2.86]	0.7%
71	1054	1191	1029	1163	1.00	[0.78; 1.29]	1.2%
29	753	785	744	776	1.01	[0.61; 1.67]	0.8%
27	1509	1544	1426	1460	1.03	[0.64; 1.66]	1.5%
86	843	872	858	889	1.05	[0.63; 1.76]	0.9%
59	1092	1113	1076	1098	1.06	[0.58; 1.94]	1.1%
98	702	721	648	667	1.08	[0.57; 2.06]	0.7%
87	811	825	747	761	1.09	[0.51; 2.29]	0.8%
84	795	953	738	900	1.10	[0.87; 1.41]	1.0%
17	662	749	694	795	1.11	[0.82; 1.50]	0.8%
72	950	990	965	1010	1.11	[0.72; 1.71]	1.0%
16	1678	1720	1688	1735	1.11	[0.73; 1.70]	1.8%
30	1016	1046	1061	1096	1.12	[0.68; 1.83]	1.1%
73	1048	1127	1003	1088	1.12	[0.82; 1.55]	1.1%
2	873	884	841	853	1.13	[0.50; 2.58]	0.9%
1	1343	1399	1344	1408	1.14	[0.79; 1.65]	1.4%
21	670	675	700	706	1.15	[0.35; 3.78]	0.7%
45	1049	1075	1077	1108	1.16	[0.68; 1.97]	1.1%
24	1189	1207	1216	1238	1.20	[0.64; 2.24]	1.3%
9	617	620	652	656	1.26	[0.28; 5.66]	0.7%
20	670	675	703	710	1.33	[0.42; 4.22]	0.7%
82	1086	1091	1112	1119	1.37	[0.43; 4.32]	1.1%
53	741	764	730	761	1.37	[0.79; 2.37]	0.8%
11	766	795	727	765	1.38	[0.84; 2.26]	0.8%
74	964	1009	978	1042	1.40	[0.95; 2.07]	1.1%
4	881	894	965	986	1.47	[0.73; 2.96]	1.0%
42	1592	1630	1530	1584	1.48	[0.97; 2.25]	1.7%
67	896	898	905	908	1.49	[0.25; 8.91]	0.9%
10	713	717	689	695	1.55	[0.44; 5.52]	0.7%
57	712	714	684	687	1.56	[0.26; 9.37]	0.7%
52	719	721	687	690	1.57	[0.26; 9.42]	0.7%
19	729	735	712	722	1.71	[0.62; 4.72]	0.8%
68	730	734	686	693	1.86	[0.54; 6.39]	0.7%
77	730	735	687	696	1.91	[0.64; 5.74]	0.7%
13	725	733	756	773	2.04	[0.87; 4.75]	0.8%
38	1053	1054	1029	1031	2.05	[0.19; 22.61]	1.1%
99	924	958	932	1003	2.07	[1.36; 3.15]	1.0%
89	670	675	641	652	2.30	[0.79; 6.85]	0.7%
46	953	960	1014	1034	2.69	[1.13; 6.38]	1.0%
7	1682	1683	1629	1632	3.10	[0.32; 29.81]	1.7%
25	753	755	807	814	3.27	[0.68; 15.77]	0.8%
100	835	841	846	868	3.62	[1.46; 8.97]	0.9%
91	627	628	656	660	3.82	[0.43; 34.30]	0.7%
63	658	659	665	671	5.94	[0.71; 49.45]	0.7%
37	1214	1214	1241	1244	6.85	[0.35; 132.71]	1.3%

Random effects model 97008 97212 0.93 [0.82; 1.06] 100.0%
 Heterogeneity: $I^2 = 14\%$, $p = 0.12$



Try Next (All Students)



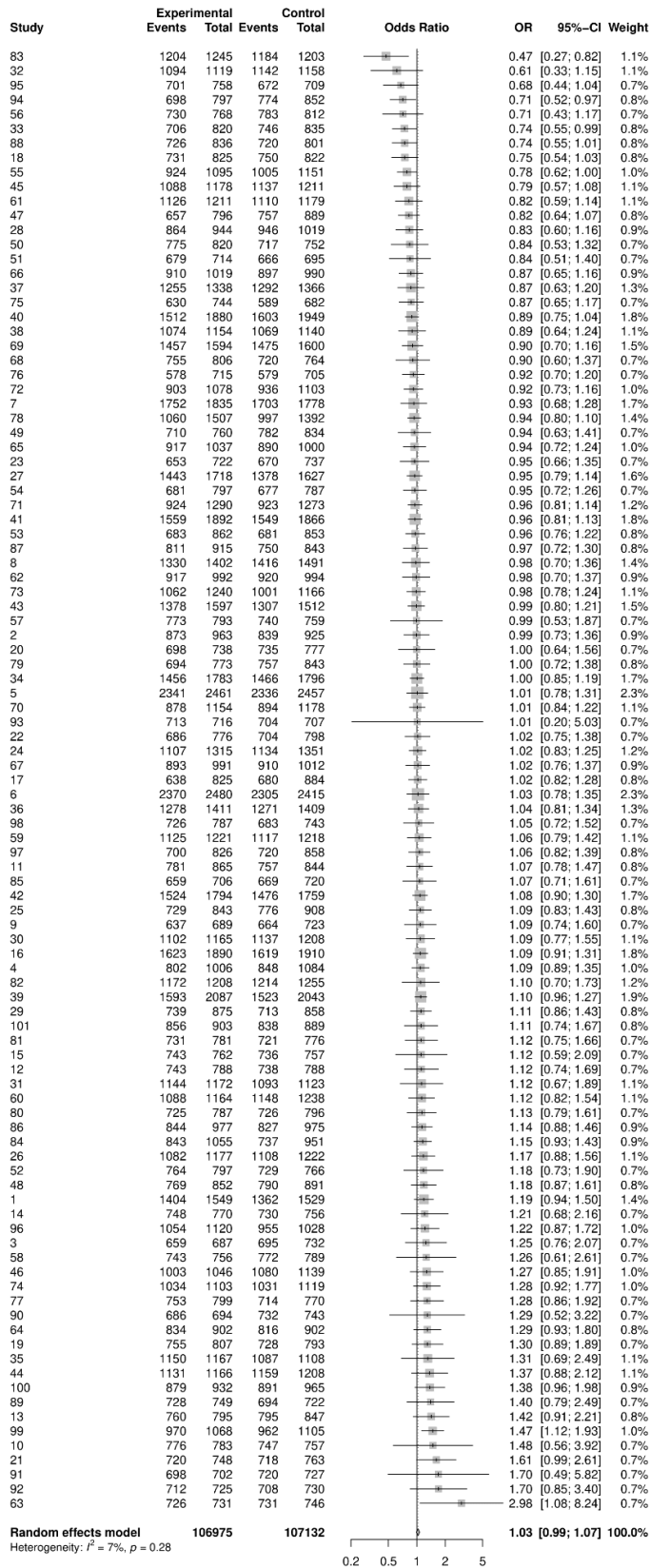
Try Next (All Previous Requesters)

Study	Experimental		Control		Odds Ratio	OR	95%-CI	Weight
	Events	Total	Events	Total				
15	709	714	691	691		0.09	[0.01; 1.69]	0.7%
93	648	650	632	632		0.21	[0.01; 4.28]	0.7%
83	1108	1127	1066	1071		0.27	[0.10; 0.74]	1.1%
66	914	919	889	891		0.41	[0.08; 2.13]	0.9%
51	626	639	625	631		0.46	[0.17; 1.22]	0.7%
32	1008	1012	1044	1046		0.48	[0.09; 2.64]	1.1%
14	710	716	692	695		0.51	[0.13; 2.06]	0.7%
65	912	928	896	906		0.64	[0.29; 1.41]	0.9%
96	1001	1023	925	938		0.64	[0.32; 1.28]	1.0%
56	674	690	723	734		0.64	[0.30; 1.39]	0.7%
22	650	698	689	722		0.65	[0.41; 1.02]	0.7%
38	1023	1054	1011	1031		0.65	[0.37; 1.15]	1.1%
34	1506	1592	1554	1612		0.65	[0.46; 0.92]	1.7%
55	930	992	988	1033		0.68	[0.46; 1.01]	1.0%
3	605	625	658	673		0.68	[0.35; 1.36]	0.7%
88	661	748	674	736		0.70	[0.50; 0.98]	0.8%
35	1050	1053	1001	1003		0.70	[0.12; 4.19]	1.1%
41	1628	1709	1627	1685		0.72	[0.51; 1.01]	1.7%
94	689	725	739	767		0.73	[0.44; 1.20]	0.8%
67	869	898	886	908		0.74	[0.42; 1.31]	0.9%
33	715	741	736	756		0.75	[0.41; 1.35]	0.8%
5	2209	2234	2221	2240		0.76	[0.42; 1.38]	2.3%
23	634	666	648	673		0.76	[0.45; 1.30]	0.7%
40	1644	1695	1722	1763		0.77	[0.51; 1.16]	1.8%
78	1158	1370	1103	1261		0.78	[0.63; 0.98]	1.4%
79	670	690	754	772		0.80	[0.42; 1.52]	0.8%
6	2214	2266	2147	2188		0.81	[0.54; 1.23]	2.3%
50	733	741	672	678		0.82	[0.28; 2.37]	0.7%
31	1061	1070	996	1003		0.83	[0.31; 2.23]	1.1%
18	723	753	721	746		0.84	[0.49; 1.43]	0.8%
49	676	688	741	752		0.84	[0.37; 1.91]	0.7%
2	841	884	817	853		0.86	[0.55; 1.36]	0.9%
75	608	675	579	634		0.86	[0.59; 1.25]	0.7%
16	1617	1720	1644	1735		0.87	[0.65; 1.16]	1.8%
80	693	712	702	719		0.88	[0.46; 1.71]	0.7%
28	815	853	892	929		0.89	[0.56; 1.41]	0.9%
95	675	698	626	645		0.89	[0.48; 1.65]	0.7%
47	668	737	744	813		0.90	[0.63; 1.27]	0.8%
82	1078	1091	1107	1119		0.90	[0.41; 1.98]	1.1%
87	782	825	725	761		0.90	[0.57; 1.42]	0.8%
85	621	632	624	634		0.90	[0.38; 2.15]	0.7%
12	700	723	703	724		0.91	[0.50; 1.66]	0.7%
101	816	826	803	812		0.91	[0.37; 2.26]	0.8%
69	1384	1449	1403	1464		0.93	[0.65; 1.32]	1.5%
43	1377	1454	1276	1343		0.94	[0.67; 1.31]	1.4%
71	995	1191	981	1163		0.94	[0.76; 1.17]	1.2%
76	546	638	558	648		0.96	[0.70; 1.31]	0.7%
27	1433	1544	1359	1460		0.96	[0.73; 1.27]	1.5%
39	1732	1887	1696	1845		0.98	[0.78; 1.24]	1.9%
97	677	750	707	782		0.98	[0.70; 1.38]	0.8%
42	1519	1630	1477	1584		0.99	[0.75; 1.31]	1.7%
70	865	1064	883	1086		1.00	[0.80; 1.24]	1.1%
72	904	990	921	1010		1.02	[0.74; 1.39]	1.0%
26	1032	1058	1084	1112		1.03	[0.60; 1.76]	1.1%
61	1085	1088	1051	1054		1.03	[0.21; 5.13]	1.1%
44	1053	1074	1066	1088		1.03	[0.57; 1.89]	1.1%
36	1228	1272	1240	1286		1.04	[0.68; 1.58]	1.3%
29	745	785	735	776		1.04	[0.66; 1.63]	0.8%
57	709	714	682	687		1.04	[0.30; 3.61]	0.7%
60	1028	1036	1108	1117		1.04	[0.40; 2.72]	1.1%
73	1021	1127	980	1088		1.06	[0.80; 1.41]	1.1%
7	1655	1683	1603	1632		1.07	[0.63; 1.81]	1.7%
24	1103	1207	1124	1238		1.08	[0.81; 1.42]	1.3%
53	707	764	700	761		1.08	[0.74; 1.57]	0.8%
17	641	749	672	795		1.09	[0.82; 1.44]	0.8%
9	590	620	621	656		1.11	[0.67; 1.83]	0.7%
92	646	655	646	656		1.11	[0.45; 2.75]	0.7%
98	681	721	626	667		1.12	[0.71; 1.75]	0.7%
90	620	625	665	671		1.12	[0.34; 3.68]	0.7%
84	784	953	725	900		1.12	[0.89; 1.42]	1.0%
62	843	897	823	883		1.14	[0.78; 1.66]	0.9%
86	826	872	836	889		1.14	[0.76; 1.71]	0.9%
30	1009	1046	1052	1096		1.14	[0.73; 1.78]	1.1%
45	1040	1075	1067	1108		1.14	[0.72; 1.81]	1.1%
8	1248	1274	1339	1371		1.15	[0.68; 1.94]	1.4%
48	710	774	733	809		1.15	[0.81; 1.63]	0.8%
54	686	705	683	705		1.16	[0.62; 2.17]	0.7%
1	1340	1399	1337	1408		1.21	[0.85; 1.72]	1.4%
81	696	711	683	701		1.22	[0.61; 2.45]	0.7%
74	953	1009	972	1042		1.23	[0.85; 1.76]	1.1%
59	1078	1113	1055	1098		1.26	[0.80; 1.98]	1.1%
11	760	795	722	765		1.29	[0.82; 2.04]	0.8%
37	1211	1214	1240	1244		1.30	[0.29; 5.83]	1.3%
20	668	675	700	710		1.36	[0.52; 3.60]	0.7%
19	723	735	706	722		1.37	[0.64; 2.91]	0.8%
21	668	675	696	706		1.37	[0.52; 3.62]	0.7%
25	704	755	740	814		1.38	[0.95; 2.00]	0.8%
52	718	721	686	690		1.40	[0.31; 6.26]	0.7%
4	875	894	956	986		1.45	[0.81; 2.59]	1.0%
77	720	735	675	696		1.49	[0.76; 2.92]	0.7%
68	725	734	680	693		1.54	[0.65; 3.63]	0.7%
100	822	841	838	868		1.55	[0.86; 2.77]	0.9%
10	713	717	689	695		1.55	[0.44; 5.52]	0.7%
64	808	815	814	825		1.56	[0.60; 4.04]	0.8%
13	719	733	749	773		1.65	[0.84; 3.21]	0.8%
46	947	960	1008	1034		1.88	[0.96; 3.68]	1.0%
58	683	684	709	711		1.93	[0.17; 21.30]	0.7%
89	666	675	634	652		2.10	[0.94; 4.71]	0.7%
99	923	958	928	1003		2.13	[1.41; 3.22]	1.0%
63	657	659	665	671		2.96	[0.60; 14.74]	0.7%
91	627	628	655	660		4.79	[0.56; 41.08]	0.7%

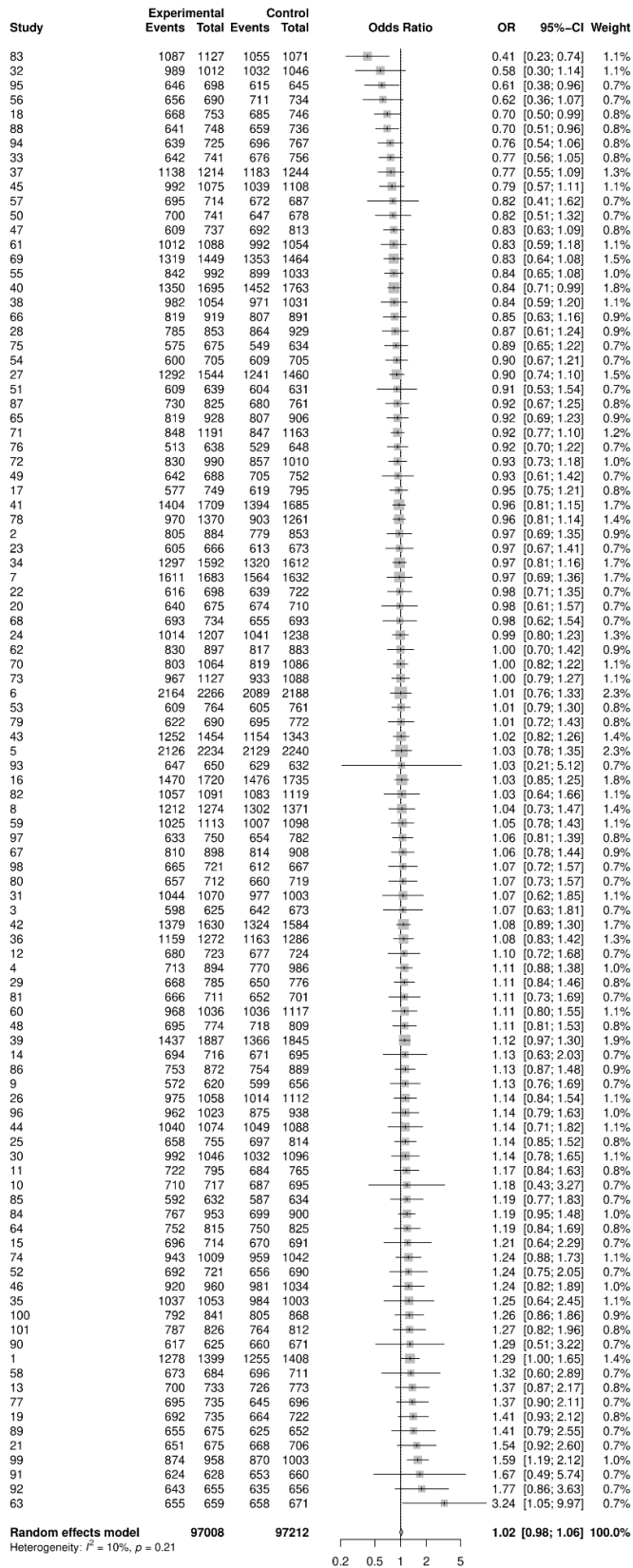
Random effects model 97008 97212 0.95 [0.87; 1.03] 100.0%
Heterogeneity: $I^2 = 8\%$, $p = 0.26$



Assignment Completed (All Students)



Assignment Completed (All Previous Requesters)



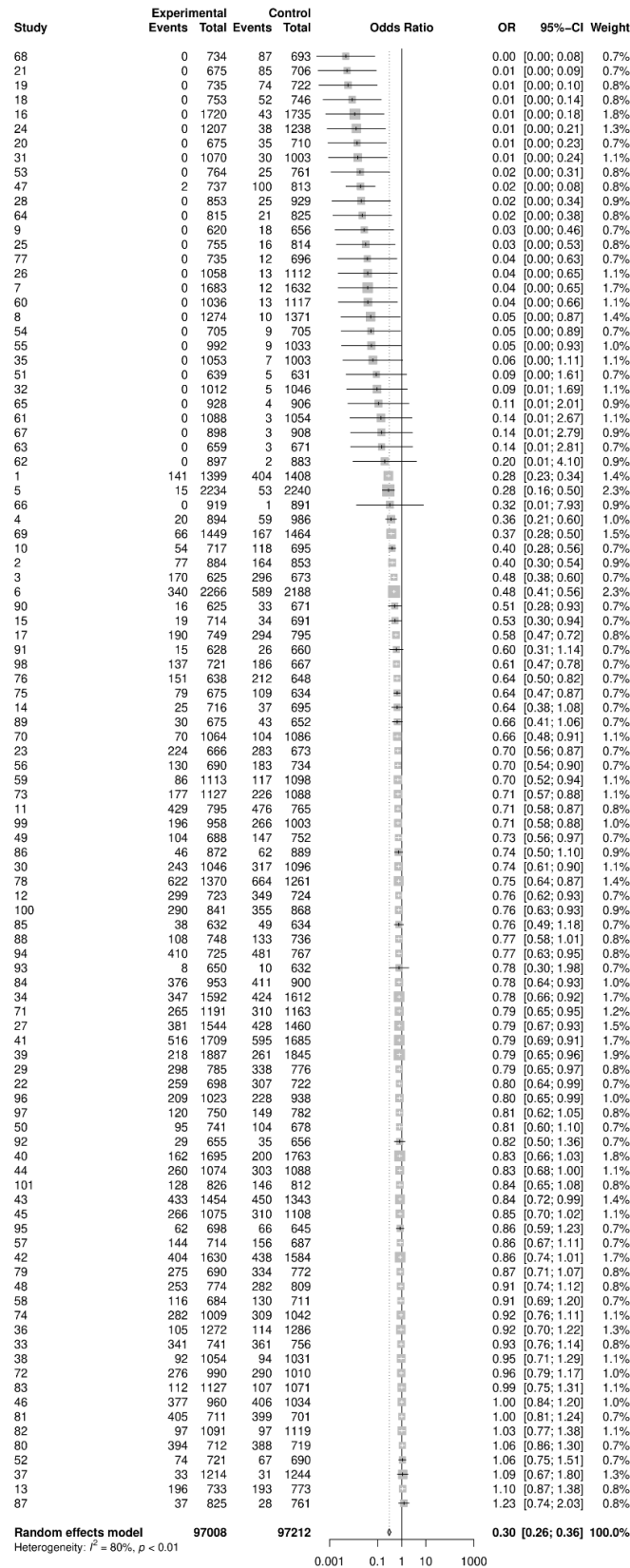
Answer Given (All Students)

Study	Experimental Events	Experimental Total	Control Events	Control Total	Odds Ratio	OR	95%-CI	Weight
68	0	806	93	764		0.00	[0.00; 0.07]	0.7%
21	0	748	92	763		0.00	[0.00; 0.08]	0.7%
19	0	807	80	793		0.01	[0.00; 0.09]	0.7%
18	0	825	60	822		0.01	[0.00; 0.12]	0.8%
16	0	1890	53	1910		0.01	[0.00; 0.15]	1.8%
24	0	1315	41	1351		0.01	[0.00; 0.20]	1.2%
20	0	738	39	777		0.01	[0.00; 0.21]	0.7%
31	0	1172	33	1123		0.01	[0.00; 0.23]	1.1%
53	0	862	28	853		0.02	[0.00; 0.28]	0.8%
47	2	796	111	889		0.02	[0.00; 0.07]	0.8%
28	0	944	28	1019		0.02	[0.00; 0.30]	0.9%
64	0	902	23	902		0.02	[0.00; 0.34]	0.8%
94	0	689	19	723		0.03	[0.00; 0.43]	0.7%
25	0	843	17	908		0.03	[0.00; 0.50]	0.8%
77	0	799	14	770		0.03	[0.00; 0.55]	0.7%
26	0	1177	14	1222		0.04	[0.00; 0.59]	1.1%
7	0	1835	13	1778		0.04	[0.00; 0.60]	1.7%
60	0	1164	13	1238		0.04	[0.00; 0.66]	1.1%
8	0	1402	11	1491		0.05	[0.00; 0.78]	1.4%
55	0	1095	10	1151		0.05	[0.00; 0.85]	1.0%
54	0	797	9	787		0.05	[0.00; 0.88]	0.7%
35	0	1167	7	1108		0.06	[0.00; 1.10]	1.1%
32	0	1119	7	1158		0.07	[0.00; 1.20]	1.1%
51	0	714	6	695		0.07	[0.00; 1.32]	0.7%
65	0	1037	5	1000		0.09	[0.00; 1.58]	1.0%
61	0	1211	4	1179		0.11	[0.01; 2.00]	1.1%
62	0	992	3	994		0.14	[0.01; 2.77]	0.9%
63	0	731	3	746		0.15	[0.01; 2.82]	0.7%
67	0	991	3	1012		0.15	[0.01; 2.82]	0.9%
1	154	1549	427	1529		0.28	[0.23; 0.35]	1.4%
5	19	2461	59	2457		0.32	[0.19; 0.53]	2.3%
66	0	1019	1	990		0.32	[0.01; 7.95]	0.9%
69	69	1594	180	1600		0.36	[0.27; 0.48]	1.5%
10	56	783	124	757		0.39	[0.28; 0.55]	0.7%
4	25	1006	65	1084		0.40	[0.25; 0.64]	1.0%
2	84	963	178	925		0.40	[0.30; 0.53]	0.9%
3	185	687	318	732		0.48	[0.38; 0.60]	0.7%
6	384	2480	654	2415		0.49	[0.43; 0.57]	2.3%
90	18	694	36	743		0.52	[0.29; 0.93]	0.7%
17	202	825	322	884		0.57	[0.46; 0.70]	0.8%
15	21	762	36	757		0.57	[0.33; 0.98]	0.7%
98	148	787	205	743		0.61	[0.48; 0.77]	0.7%
14	26	770	41	756		0.61	[0.37; 1.01]	0.7%
75	89	744	120	682		0.64	[0.47; 0.86]	0.7%
91	17	702	27	727		0.64	[0.35; 1.19]	0.7%
70	73	1154	111	1178		0.65	[0.48; 0.88]	1.1%
59	90	1221	128	1218		0.68	[0.51; 0.90]	1.1%
76	178	715	231	705		0.68	[0.54; 0.86]	0.7%
11	455	865	520	844		0.69	[0.57; 0.84]	0.8%
56	142	768	198	812		0.70	[0.55; 0.90]	0.7%
89	56	749	48	722		0.71	[0.45; 1.11]	0.7%
73	191	1240	236	1166		0.72	[0.58; 0.89]	1.1%
23	244	722	304	737		0.73	[0.59; 0.90]	0.7%
29	319	875	376	858		0.74	[0.61; 0.89]	0.8%
99	220	1068	288	1105		0.74	[0.60; 0.90]	1.0%
94	444	797	535	852		0.75	[0.61; 0.91]	0.8%
27	416	1718	486	1627		0.75	[0.64; 0.87]	1.6%
34	390	1783	487	1796		0.75	[0.65; 0.88]	1.7%
100	318	932	393	965		0.75	[0.63; 0.91]	0.9%
78	688	1507	733	1392		0.76	[0.65; 0.87]	1.4%
22	281	776	341	798		0.76	[0.62; 0.93]	0.7%
49	114	760	157	834		0.76	[0.58; 0.99]	0.7%
30	273	1165	345	1208		0.77	[0.64; 0.92]	1.1%
86	54	977	68	975		0.78	[0.54; 1.13]	0.9%
12	325	788	373	788		0.78	[0.64; 0.95]	0.7%
39	238	2087	289	2043		0.78	[0.65; 0.94]	1.9%
84	421	1055	435	951		0.79	[0.66; 0.94]	0.9%
71	285	1290	336	1273		0.79	[0.66; 0.95]	1.2%
88	123	836	143	801		0.79	[0.61; 1.03]	0.8%
96	222	1120	242	1028		0.80	[0.65; 0.99]	1.0%
41	564	1892	644	1866		0.81	[0.70; 0.92]	1.8%
97	131	826	162	858		0.81	[0.63; 1.04]	0.8%
85	44	708	54	720		0.82	[0.54; 1.24]	0.7%
43	469	1597	508	1512		0.82	[0.71; 0.96]	1.5%
50	105	820	114	752		0.82	[0.62; 1.09]	0.7%
44	279	1166	334	1208		0.82	[0.68; 0.99]	1.1%
57	157	793	173	759		0.84	[0.66; 1.07]	0.7%
95	65	758	70	709		0.86	[0.60; 1.22]	0.7%
45	287	1178	329	1211		0.86	[0.72; 1.04]	1.1%
40	183	1880	216	1949		0.87	[0.70; 1.07]	1.8%
101	141	903	155	889		0.88	[0.68; 1.12]	0.8%
42	444	1794	476	1759		0.89	[0.76; 1.03]	1.7%
48	275	852	311	891		0.89	[0.73; 1.08]	0.8%
38	98	1154	107	1140		0.90	[0.67; 1.19]	1.1%
92	34	725	38	730		0.90	[0.56; 1.44]	0.7%
93	10	716	11	707		0.90	[0.38; 2.12]	0.7%
36	116	1411	128	1409		0.90	[0.69; 1.17]	1.3%
74	302	1103	329	1119		0.91	[0.75; 1.09]	1.0%
79	311	773	358	843		0.91	[0.75; 1.11]	0.8%
72	299	1078	323	1103		0.93	[0.77; 1.12]	1.0%
58	126	756	139	769		0.94	[0.72; 1.22]	0.7%
83	124	1245	123	1203		0.97	[0.75; 1.26]	1.1%
33	379	820	390	835		0.98	[0.91; 1.19]	0.8%
80	426	787	429	796		1.01	[0.83; 1.23]	0.7%
46	402	1046	433	1139		1.02	[0.86; 1.21]	1.0%
52	81	797	75	766		1.04	[0.75; 1.45]	0.7%
82	106	1208	106	1255		1.04	[0.79; 1.38]	1.2%
37	38	1338	37	1366		1.05	[0.66; 1.66]	1.3%
13	206	795	207	847		1.08	[0.87; 1.35]	0.8%
81	452	781	428	776		1.12	[0.91; 1.37]	0.7%
87	40	915	33	843		1.12	[0.70; 1.80]	0.8%

Random effects model 106975 107132 0.30 [0.25; 0.35] 100.0%
 Heterogeneity: $I^2 = 81\%$, $p < 0.01$



Answer Given (All Previous Requesters)



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