

Effect of Learning Feedback Styles on Learning Outcomes

Fall 2020 - W241 Final Report

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Load Data

```
d_respondents <- fread('datatable_clean_survey_responses_v2.dta')
```

Functions

```
get_robust_se <- function(model){  
  # Get robust SE for use in stargazer  
  vcov <- vcovHC(model,type = "HC1")  
  return(sqrt(diag(vcov)))  
}  
  
create_heatmap <- function(var1, var2) {  
  ### Create a heatmap for a table of frequencies between two variables ###  
  df <- data.frame(table(var1,var2))  
  
  ggplot(df,aes(x=var1,y=var2)) +  
    geom_tile(aes(fill=Freq,color=Freq),show.legend=FALSE,alpha=.8) +  
    geom_text(aes(label=Freq)) +  
    theme(axis.text.x = element_text(angle = 90)) +  
    scale_fill_continuous(high = "darkslategray4", low = "powderblue")  
}
```

Abstract

Background

Whether its the coach and player, teacher and pupil, or manager and entry-level employee, feedback likely plays an important role in delivering successful outcomes. All managerial figures are encouraged to give feedback as understudies are likewise encouraged to receive critique openly. However, what is good feedback and how much of one's success can be attributed to this feedback? Suprisingly few, well-developed experiments have been conducted to investigate this relationship. In this study, we seek to better understand if feedback truly influences successful outcomes and if different types of feedback lead to better outcomes than others.

Research Question

Our research highlights the broad field of research around the role of feedback on performance. Successful feedback is thought to lead to improved performance. However it is too broad of a question for an experiment

to point to a causal claim. Exogenous factors such as the learning environment, the learner’s psychological mentality, or the type of task being taught may come into play in an non-experimental analysis.

Additionally, feedback comes in all different styles, both positive and negative, internal and external. Some types of critique may be better than others, while others may actually be detrimental to one’s performance. As such, a well-designed experiment is necessary to find a true (if any) causal effect on learning outcomes.

The scope of our experiment is, as a result, intentionally narrow to measure the effect of different types of feedback on task performance. In our design, we ask survey respondents to recognize if an x-ray image shows healthy lungs or lungs with pneumonia. This study introduces a novel concept to most, if not all subjects, requires strenuous mental thought, and makes several extraneous elements consistent throughout the learning process (i.e. the computer-based learning environment, the feedback types, and the question being asked are the same throughout the program).

Hypothesis

The research question in this experiment attempts to answer the following question:

What type of feedback (positive reinforcement, negative reinforcement, self-reflective, etc.) leads to the largest improvements in individual performance within a simple, recognition-based task, if any?

We are testing the null hypothesis that the varying types of feedback do not lead to better outcomes. To generalize, we then test if the average treatment effect between those who receive any feedback and those who receive a placebo will equal 0.

A related follow-up question addresses:

Does more frequent feedback yield higher task performance?

We anticipate that more feedback touchpoints will associate with better individual performance because the receiver has more insight into how to improve and is able to calibrate to meet and surpass previous performance thresholds. However, it is unclear if the marginal gains from the second feedback loop will be as meaningful as the first.

Experimental Design

Overview

This design follows a difference-in-differences design and is implemented through regression adjustment. Participants completed a three-part survey in one sitting. The random assignment occurs after the first round of questions, which allows us to pre-screen for compliance. The core analysis compares the difference in scores between the first iteration (pre-treatment) and the second iteration (post first treatment) scores in order to test the immediate effects of feedback on performance. We further compare the first iteration scores with the third iteration (post second treatment) scores to understand the effect of repeated feedback.

In this experiment, participants will view a set of X-Ray slides. Each slide contains an X-Ray image of a patient’s lungs. The participant will have to determine if the patient’s lungs are healthy or have pneumonia. Responses and timings will be recorded. Three rounds will create an answer set of 30 images (3 Rounds x 10 X-Ray images in each round). Each intervention type, while limited in scope to the X-Ray recognition task, is meant to replicate a real-life style of feedback. Participants will be randomly assigned to the following control or treatment groups, with two one-minute breaks in between sessions.

- *Control* - Subject watches a pharmaceutical video and is asked how the video makes them feel. This replicates the experience of someone that does not receive any internal or external feedback.
- *Self Reflective Treatment* - Subject is shown the last round’s images, their answers, and the correct answers. They are then asked to reflect in two sentences about how they can improve. This reflects someone who does not receive feedback from others but thinks critically about their own performance and how to improve.

- *Positive Reinforcement Treatment* - Subject is shown the images of the last round’s healthy lungs only and is asked to study those images for 1 minute. This reflects someone who is only told the positive aspects of their performance.
- *Negative Reinforcement Treatment* - Subject is shown the images of the last round’s pneumonia-filled lungs only and is asked to study those images for 1 minute. This reflects someone who is only told the negative aspects of their performance.
- *Specific Feedback Treatment* - Subject is shown the last round’s images, their answers, and the correct answers. They are then given easy-to-digest information from a medical textbook on how to spot pneumonia. This reflects a situation where someone is given expert-driven advice on how to accomplish a task.

Project Timeline

The project was conducted on the following timeline:

<i>Experiment Ideation & Design</i>			<i>Data Collection & Final Analysis Presentation Final Report</i>		
	<i>Trial Survey</i>	<i>Survey Period</i>			
Oct. 28 - Nov. 5	Nov. 6 - 8	Nov. 9 - 14	Nov. 15 - 30	Dec. 8	Dec. 15

Enrollment and Recruitment Process

Subjects were recruited through Mechanical Turk and received \$1 upon successful completion. Multiple entries from the same respondent were not permitted. Mechanical Turk lists the survey in a pool of others and payouts were given by the research team after successful completion of the survey. We ended up receiving 447 survey submissions. Since we charged a relatively high price point per survey, we were able to receive all of these responses in a matter of 72 hours. This may have worked in our favor by mitigating time-series related effects in the resulting data, **however it also included several drawbacks mentioned later in the paper.**

Subjects were mostly from the United States (225) and India (115). There were more males that participated in the study (207) than females (143).

Communication and Measurement Tooling

The experiment recruited participants from Mechanical Turk, who were then given a link to the survey on Qualtrics. They were asked to enter their MTurk Worker ID and complete demographic questions before starting the survey. Friends and family were used to test the experiment flow, however none were known to have taken the full experiment, nor were part of our final analysis. The survey was compatible with both mobile and desktop applications. This helped reduce the barrier to entry for the survey. To help prevent non-compliance, we mandated timings on the treatment phases so that each subject fully received treatment.

Randomization

Because subjects are recruited from Mechanical Turk, we have access to a global workforce pool. Then, participants were randomly assigned to each of the 5 groups based on randomization logic pre-built on the Qualtrics system. Randomization occurred through the Qualtrics system after the first pre-treatment phase and split the remaining responses evenly between the four treatment groups and the control group. This randomization process is important so that treatment assignments are independent of subjects’ potential outcomes. Furthermore, unaccounted-for covariates of the subject pool would not bias our estimate of the ATE. The Qualtrics flow can be seen below.

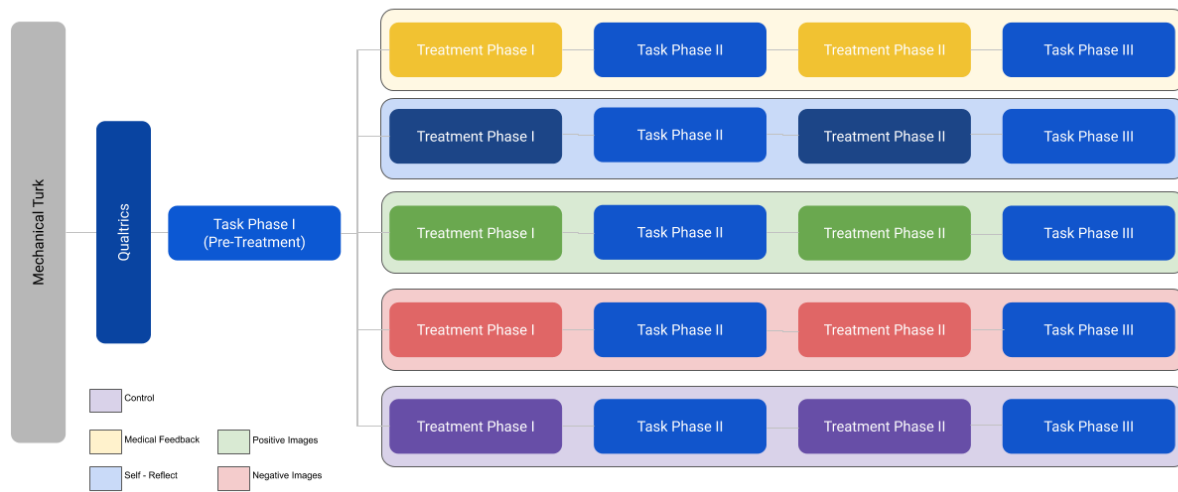


Figure 1: Qualtrics Flow

Excludability and Non-Interference

This design also meets the excludability and non-interference assumptions needed to provide an unbiased estimate of the average treatment effect. Once a subject is assigned a treatment group, he or she receives a specific treatment for two separate times since treatment phases alternate with task phases II and III. We meet the excludability assumption since outcomes are measured consistently through all task phases and for all assignment groups. Every task phase is scored on a scale from 1 to 10. Thus, what one subject scored in pre-treatment can be directly compared to what he or she scored in post-treatment. Furthermore, subjects are asked to essentially make diagnoses from looking at x-ray images. We believe that this is an esoteric topic, which would make it difficult for respondents to perform third-party research while completing the survey. However, we are better able to answer this subject by looking at the completion times below.

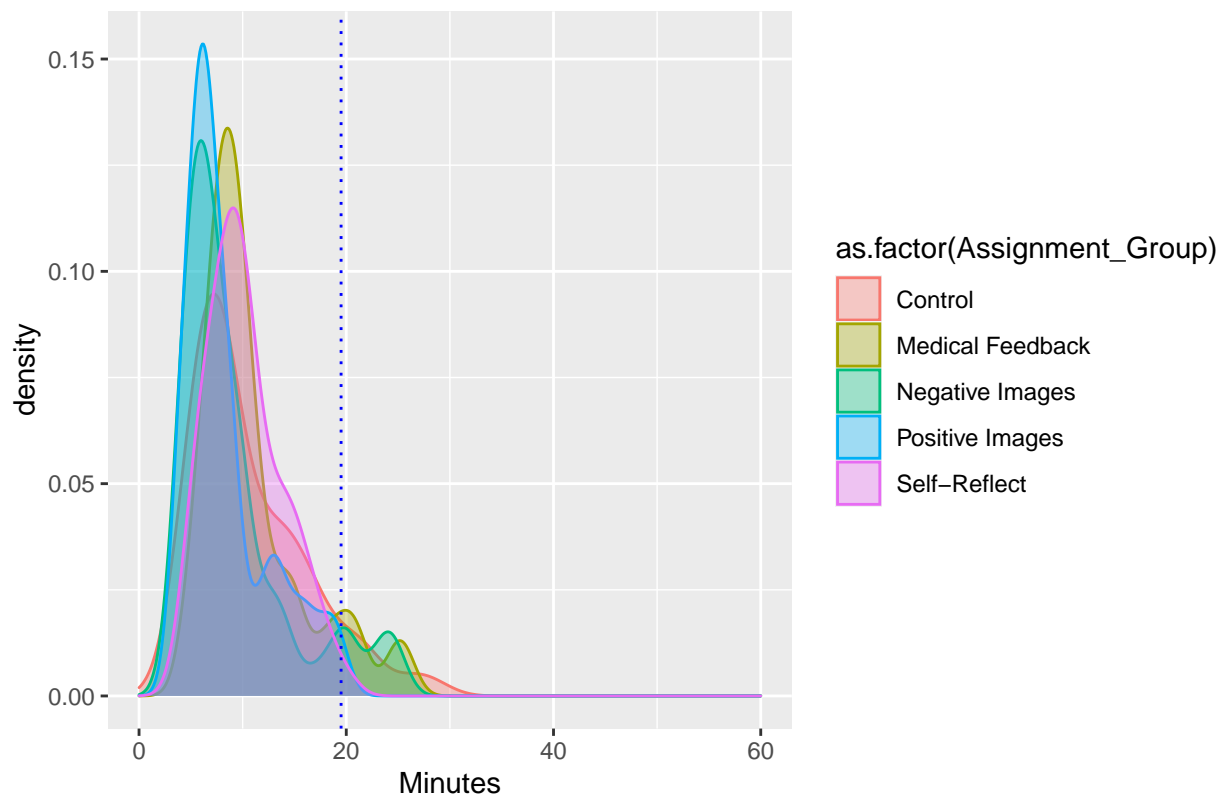
```

#n survey responses > 30 mins., take outlier out for analysis but discuss below
outlier <- round(d_respondents[`Duration (in seconds)` > 60*30, `Duration (in seconds)`/60/60],1)
completions <- d_respondents[`Duration (in seconds)` < 60*30]

#95% of participants finished below this point in mins.
upper_cl <- completions[, round(mean(`Duration (in seconds)`)/60) + (2 *(sd(`Duration (in seconds)`)/60)

#density plot of time completed by assignment group in mins.
ggplot(completions, aes(x=`Duration (in seconds)`/60, fill = as.factor(Assignment_Group), colour=as.factor(Assignment_Group))) +
  geom_density(alpha = 0.35) +
  xlim(0,60) +
  ggtitle("Survey Duration by Assignment Group (sans Outlier)") +
  labs(x = "Minutes") +
  geom_vline(xintercept = upper_cl, linetype="dotted", color = "blue", size = 0.5) +
  theme(plot.title = element_text(hjust = 0.5))
  
```

Survey Duration by Assignment Group (sans Outlier)



We had one entry that took 4.9 hours to complete the survey. This could be due to research but is likely due to other factors such as just leaving the computer idle up for certain period of time. Eliminating this outlier, 95% of participants completed the survey in 19.5 minutes or less. As such, subject driven, third-party research did not likely play a role in outcomes. The non-interference assumption is also met in this experiment since subjects are not aware of the treatments in other groups. They also do not know each other and cannot share about their treatment status with untreated subjects or vice versa.

Covariate Balance Checks

We check how well our randomization worked by checking that the proportion of individuals assigned to each group was similar. Furthermore, we performed visual covariate balance checks on the survey data as it relates to gender, age range, education, and country. We additionally performed Chi Squared Tests for Independence to test for independence within each of these categories. None of the Chi-Squared tests were significant at the $p = .05$ level, signaling that there is no relationship between these covariates and the treatment and control assignment groups. Proportions of each covariate were consistent across assignment groups.

```
create_heatmap <- function(var1, var2) {
  ### Create a heatmap for a table of frequencies between two variables ###
  df <- data.frame(table(var1,var2))

  ggplot(df,aes(x=var1,y=var2)) +
    geom_tile(aes(fill=Freq,color=Freq),show.legend=FALSE,alpha=.8) +
    geom_text(aes(label=Freq)) +
    theme(axis.text.x = element_text(angle = 90)) +
    scale_fill_continuous(high = "darkslategray4", low = "powderblue")
}

# check balance between assignment groups
```

```

d_respondents %>%
  group_by(Assignment_Group) %>%
  summarise(count = n())

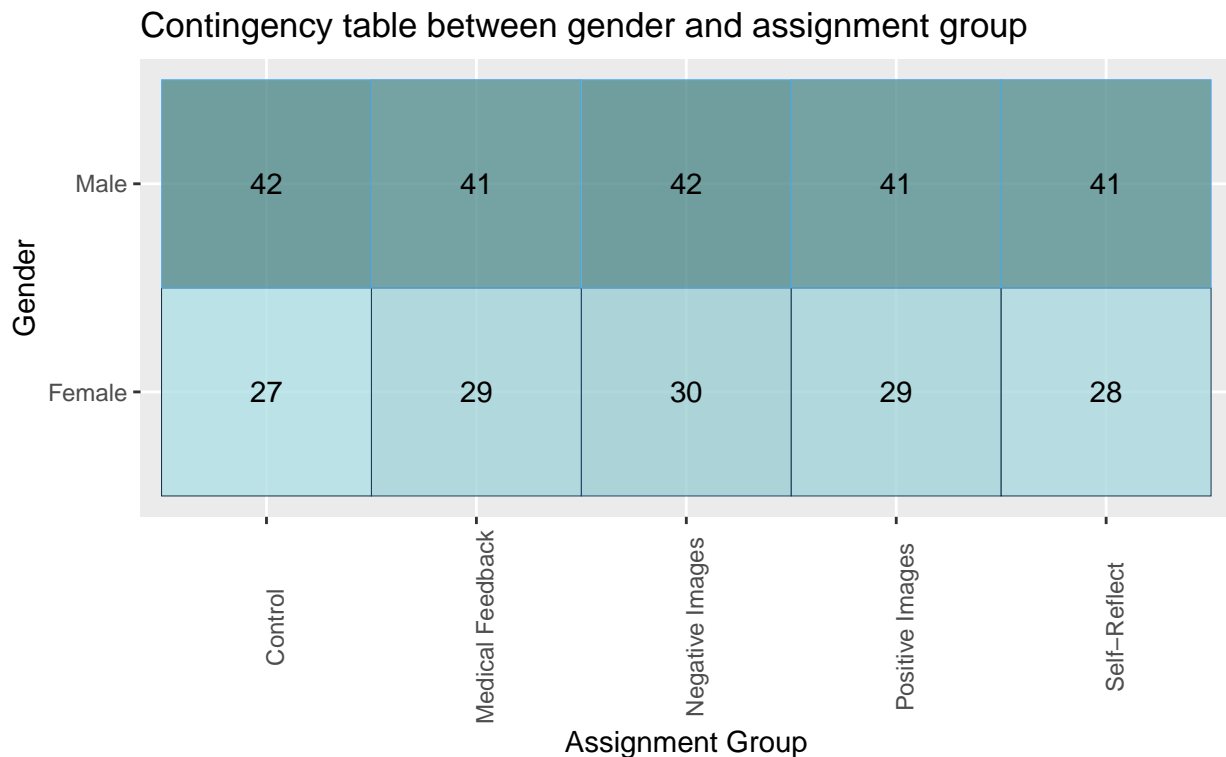
## `summarise()` ungrouping output (override with `.groups` argument)

## # A tibble: 5 x 2
##   Assignment_Group count
##   <chr>             <int>
## 1 Control           69
## 2 Medical Feedback  70
## 3 Negative Images   72
## 4 Positive Images   70
## 5 Self-Reflect      69

# check balance between genders
gender_chiqr <- chisq.test(d_respondents[, table(Assignment_Group, Gender)])

create_heatmap(var1 = d_respondents$Assignment_Group, var2 = d_respondents$Gender) +
  xlab('Assignment Group') +
  ylab('Gender') +
  labs(title = 'Contingency table between gender and assignment group',
       caption = paste0('Assuming gender distributions are the same among assignment groups, a chi-squared test for independence with',
                        round(gender_chiqr$parameter, 4), ' \ndegrees of freedom ', 'yields p=',
                        round(gender_chiqr$p.value, 4),
                        ', suggesting that there is no relationship between gender and assignment group'))
  theme(plot.caption = element_text(hjust = 0))

```



```
# check balance between age ranges
age_chisq <- chisq.test(d_respondents[ , table(Assignment_Group, Age_Range)],simulate.p.value = TRUE)

create_heatmap(var1 = d_respondents$Assignment_Group,var2 = d_respondents$Age_Range) +
  xlab('Assignment Group') +
  ylab('Age Range') +
  labs(title = 'Contingency table between age range and assignment group',
       caption = paste0('Assuming age distributions are the same among assignment groups, a chi-squared
                          round(age_chisq$p.value,4),
                          ', suggesting that there is no relationship between age and assignment groups a
  theme(plot.caption = element_text(hjust = 0))
```

Contingency table between age range and assignment group

Age Range	Control	Medical Feedback	Negative Images	Positive Images	Self-Reflect
Above 65	0	2	0	0	1
55-64	9	6	5	11	8
45-54	7	4	9	5	11
35-44	11	15	16	20	10
25-34	37	38	38	31	36
18-24	5	5	4	3	3

Assuming age distributions are the same among assignment groups, a chi-squared test for independence Carlo simulation yields $p=0.5062$, suggesting that there is no relationship between age and assignment significance level of 0.05.

```
#check balance between education levels
edu_chisq <- chisq.test(d_respondents[ , table(Assignment_Group, Education_Level)],simulate.p.value = TRUE)

create_heatmap(var1 = d_respondents$Assignment_Group,var2 = d_respondents$Education_Level) +
  xlab('Assignment Group') +
  ylab('Education Level') +
  labs(title = 'Contingency table between education and assignment group',
       caption = paste0('Assuming education distributions are the same among assignment groups, a chi-squared
                          round(edu_chisq$p.value,4),
                          ', suggesting that there is no relationship \n between education and assignment g
  theme(plot.caption = element_text(hjust = 0))
```

Contingency table between education and assignment group

Education Level	Trade school	1	1	3	2	1
	Some high school	0	0	1	0	0
	Master's degree and above	20	14	13	19	11
	High school	1	1	3	0	7
	Bachelor's degree	44	54	50	45	46
	Associate's degree	3	0	2	4	4
		Control	Medical Feedback	Negative Images	Positive Images	Self-Reflect
		Assignment Group				

Assuming education distributions are the same among assignment groups, a chi-sq independence with Monte Carlo simulation yields $p=0.068$, suggesting that there is no relationship between education and assignment groups at a significance level of 0.05.

```
# check balance between US and non-US respondents
us_chisq <- chisq.test(d_respondents[, table(Assignment_Group, US_Dummy)])

create_heatmap(var1 = d_respondents$Assignment_Group, var2 = d_respondents$US_Dummy) +
  xlab('Assignment Group') +
  ylab('Country') +
  scale_y_discrete(breaks=c("0", "1"),
    labels=c("Non-US", "United States")) +
  labs(title = 'Contingency table between country and assignment group',
    caption = paste0('Assuming country distributions are the same among assignment groups, a chi-square test with Monte Carlo simulation yields p = ',
      round(us_chisq$parameter, 4), ' degrees of freedom ', 'yields p = ',
      round(us_chisq$p.value, 4),
      ', suggesting that there is no relationship between country and assignment \n groups at a significance level of 0.05.')
  theme(plot.caption = element_text(hjust = 0))
```


Contingency table between country and assignment group

Country	Assignment Group				
	Control	Medical Feedback	Negative Images	Positive Images	Self-Reflect
United States	45	37	45	50	48
Non-US	24	33	27	20	21

Assuming country distributions are the same among assignment groups, a chi-squared test for independence with 4 degrees of freedom yields $p=0.1647$, suggesting that there is no relationship between country and assignment groups at a significance level of 0.05.

Observation and Outcome Measurables

The data we collected was exported directly from Qualtrics into a CSV file. Data was then cleaned in R and exploratory data analysis was performed to check out data points. In all, we collected the following categorical data:

- Metadata - Entry data such as start and end dates, IP Addresses, Locations, Duration, Survey Status (Finished, Incomplete)
- Demographic Data - Age Range, Education Level, Gender
- Assignment Group - Control, Positive Images, Negative Images, Self-Reflection, and Medical Feedback
- Responses - Survey responses for Task Phase 1 (questions 1 - 10), Task Phase 2 (questions 11 - 20), and Task Phase 3 (questions 21 - 30)
- Scores - Scores for Task Phase 1, Task Phase 2, Task Phase 3 (out of 10); treatment scores combining Task Phases 2 and 3 (out of 10); cumulative scores (out of 30)

Our outcome measurable follows a difference in differences design. Scoring is based on number of questions a person gets right out of 10 questions per phase. This is then converted to a percentage value so that it will be easier to analyze regression results. So in this case, a 10 percentage point increase in performance would signify getting 1 additional question right. We will assess three main regressions with the following outcome variables: Task Phase 2 Scores and Task Phase 3 Scores.

We will focus on two major comparisons. 1. Control vs. All Treatment Groups: This compares people who receive the control with people who receive any form of feedback treatment. 2. Individual Treatment Effects: This second comparison focuses on comparing each individual treatment group with the control and with each other. ***DO WE FOCUS ON THE MARGINAL EFFECT OF THE SECOND FEEDBACK LOOP VS. THE FIRST FEEDBACK LOOP***

Data Completeness

The experiment started off with 381 surveys sourced through MTurk. Off this initial batch of participants, some submitted multiple responses in order to try to take advantage of our higher than average survey price point. We included only their initial surveys, throwing out 4 responses. One person also had not done the survey but had only submitted a fake MTurk code. Additionally, 37 surveys had blatantly input incorrect answers in one or more sections. This includes survey participants who marked responses in all one answer (e.g. all healthy) or alternating answers throughout the survey (e.g. healthy, pneumonia, healthy, pneumonia, etc.). We treated these participants as non-compliers.

Out of this participant pool, we threw out 97 results. These results were thrown out for the following reasons:

1. Clear non-compliance ($n = 44$): Some participants did not give honest effort on the survey and answered all “Normal”, all “Pneumonia”, or all alternating responses. These were also thrown out of the analysis.
2. Multiple submissions and non-valid entries ($n = 5$): The research team’s \$1.00 per survey price point was relatively high. As a result, some participants tried to send in multiple survey responses to collect multiple payments or submit an invalid MTurk code. In these instances we only paid for (and used) the first survey.
3. Incomplete surveys ($n = 66$): Some people started surveys but never finished. This includes those who never completed the last step of the survey, by closing out their answers. These responses were thrown out and attrition is dealt with in the survey results shown below.

Attrition occurred at several steps in the survey. 14 dropped off before Task Phase I while collecting demographic information and while entering the MTurk code (did not receive treatment assignment). 20 dropped the survey during the 10 image set in Task Phase I or during the first treatment phase. 7 dropped off during Task Phase II or during the second treatment phase. 4 dropped out during Task Phase 3 and 21 of these participants had made 99% progress but had failed to close the survey. However, we treated all 66 of the aforementioned incomplete survey responses as part of attrition and were not part of our final analysis. A funnel diagram below shows the participant drop offs of each type and at each level of the experiment:

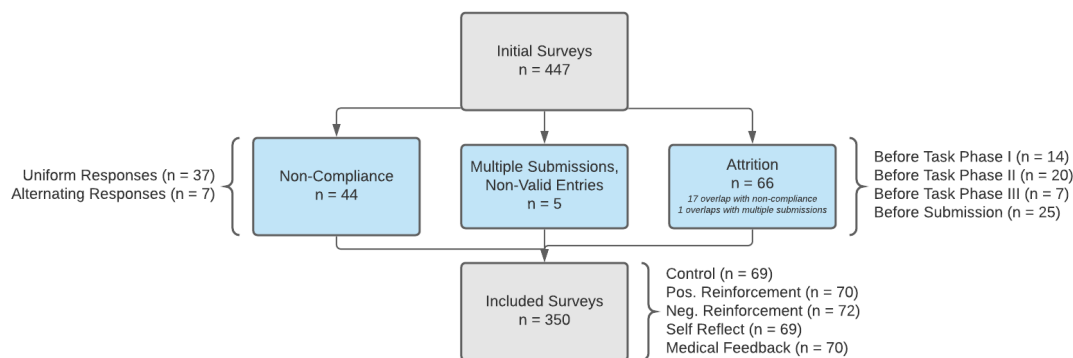


Figure 2: Survey Funnel Diagram Flow

Results

Overall, we have multiple ways we could have assessed this data based on our different treatment groups. We’ll primarily focus on two major comparisons.

Control vs. all treatment groups. This compares people who receive the control with people who receive any form of feedback treatment.

The second comparison focuses on comparing each individual treatment group with the control and with each other.

Regressions

```
# does any treatment have an effect on task phase 2 score?
mod_task2_a <- d_respondents[, lm(TaskPhase2_Score ~ Treatment_Dummy)]

mod_task2_b <- d_respondents[, lm(TaskPhase2_Score ~ Treatment_Dummy +
                                TaskPhase1_Score +
                                as.factor(Gender) +
                                as.factor(Education_Level) +
                                as.factor(Age_Range))]

stargazer(mod_task2_a,
           mod_task2_b,
           se = list(get_robust_se(mod_task2_a), get_robust_se(mod_task2_b)),
           omit = c("Education_Level", "Age_Range"),
           add.lines = list(c('Education Fixed Effects', 'No', 'Yes'),
                           c('Age Fixed Effects', 'No', 'Yes')),
           header=FALSE,
           type='latex')
```

Table 2:

	<i>Dependent variable:</i>	
	TaskPhase2_Score	
	(1)	(2)
Treatment_Dummy	0.053** (0.022)	0.051** (0.022)
TaskPhase1_Score		0.240*** (0.047)
as.factor(Gender)Male		-0.010 (0.017)
Constant	0.461*** (0.019)	0.281*** (0.072)
Education Fixed Effects	No	Yes
Age Fixed Effects	No	Yes
Observations	350	350
R ²	0.017	0.117
Adjusted R ²	0.014	0.083
Residual Std. Error	0.163 (df = 348)	0.158 (df = 336)
F Statistic	5.911** (df = 1; 348)	3.433*** (df = 13; 336)

Note:

*p<0.1; **p<0.05; ***p<0.01

```
#does the specific treatment group have an effect on task phase 2 score?
mod_task2_c <- d_respondents[, lm(TaskPhase2_Score ~ as.factor(Assignment_Group))]

mod_task2_d <- d_respondents[, lm(TaskPhase2_Score ~ as.factor(Assignment_Group) +
                                TaskPhase1_Score +
```

```

as.factor(Gender) +
as.factor(Education_Level) +
as.factor(Age_Range)]

#stargazer output
stargazer(mod_task2_c,
  mod_task2_d,
  se = list(get_robust_se(mod_task2_c), get_robust_se(mod_task2_d)),
  omit = c("Education_Level", "Age_Range"),
  add.lines = list(c('Education Fixed Effects', 'No', 'Yes'),
    c('Age Fixed Effects', 'No', 'Yes')),
  header=FALSE,
  type="latex")

```

Table 3:

	<i>Dependent variable:</i>	
	TaskPhase2_Score	
	(1)	(2)
as.factor(Assignment_Group)Medical Feedback	0.062** (0.027)	0.055* (0.029)
as.factor(Assignment_Group)Negative Images	0.034 (0.027)	0.039 (0.027)
as.factor(Assignment_Group)Positive Images	0.053* (0.029)	0.050* (0.027)
as.factor(Assignment_Group)Self-Reflect	0.065** (0.028)	0.058** (0.029)
TaskPhase1_Score		0.238*** (0.048)
as.factor(Gender)Male		-0.010 (0.017)
Constant	0.461*** (0.019)	0.282*** (0.073)
Education Fixed Effects	No	Yes
Age Fixed Effects	No	Yes
Observations	350	350
R ²	0.021	0.119
Adjusted R ²	0.010	0.076
Residual Std. Error	0.164 (df = 345)	0.158 (df = 333)
F Statistic	1.874 (df = 4; 345)	2.805*** (df = 16; 333)

Note:

*p<0.1; **p<0.05; ***p<0.01

```

pander(anova(mod_task2_b, mod_task2_d, test='F'), style='rmarkdown')

```

Table 4: Analysis of Variance Table

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
336	8.338	NA	NA	NA	NA
333	8.323	3	0.01439	0.1919	0.9019

In our first experiment, we hoped to answer whether giving feedback will immediately impact task performance. As such, this model compares Phase 2 task performance results where the subjects have only received 1 round of treatment or placebo.

In the left table you see, we wanted to condense cells into assessing “any feedback” by creating a treatment dummy variable. We reasoned that in the real world, managers may have diverse ways of giving feedback, but at the end of the day, the direct reports are still receiving ways to understand their past performance and how to improve. Therefore, we want to roll up to a treatment dummy regression to test out this theory.

As we look at the second column of this table that contains our covariates (pre-treatment score, Gender, FE from education and age), we see that we experience a 5.1 percentage point increase in task performance when any feedback is given to the survey respondents, which is statistically significant given robust SE of 2.2. What is notable, though, is that adding in these covariates does not severely change our estimate for the effect of feedback and we do not see a marginal decrease in SE, so our estimate is no more precise when controlling for these other variables. As a gut check, we see that each 10% increase in Task Phase 1 scores is associated with a 2.4 percentage point increase in performance, which resonates with us; people who perform well before feedback may also perform well after feedback.

Building off these results, we were further interested in exploring what type of feedback would yield the most positive impact on task performance. In this way, we were hoping to inform managers what type of feedback they should use with their direct reports. We believed that medical feedback would yield the most benefit because not only do you get information on what you got wrong but you also received expert opinion on how to properly assess the images. Abstracting this out to the real world, this would be akin to having a manager act as a mentor and using their experiences to enable your success. At a high level, we see that when people receive medical feedback, they experience a 5.5 percentage point increase in performance that is statistically significant, thereby confirming our hypothesis.

We hypothesized that the negative images feedback would fare the worst because we are only sharing their responses on the pneumonia images and whether they got them right or wrong. In this way, we wanted to simulate when a manager focuses on giving feedback only in abnormal situations. As a result, direct reports may have a poorer understanding of what “normal” or “good” looks like. Taking a look at that estimate, we see that people in the negative image feedback group have only a 3.9 percentage point increase that is not statistically significant, indicating that negative feedback was not helpful in improving performance.

Somewhat surprisingly, we found that people who were asked to self-reflect on their responses had a statistically significant 5.8 percentage point increase in performance. We were primarily interested in pursuing this type of feedback because it is a common personal growth technique to self-reflect that is touted in articles in HBR, Forbes, etc. In this way, we were able to confirm the positive effects of self-reflection; as a manager, you might encourage this behavior through incorporating self-assessments.

Lastly, was this necessary to blow out this analysis to the multiple treatment groups? An F-test suggests that expanding on the treatment groups as shown in the table on the right yields a model that better represents this data.

```
# test final task and any treatment
mod_task3_a <- d_respondents[, lm(TaskPhase3_Score ~ Treatment_Dummy)]
mod_task3_b <- d_respondents[, lm(TaskPhase3_Score ~ Treatment_Dummy +
                                   TaskPhase1_Score +
                                   as.factor(Gender) +
                                   as.factor(Education_Level) +
```

```

as.factor(Age_Range)])

stargazer(mod_task3_a,
  mod_task3_b,
  se = list(get_robust_se(mod_task3_a),get_robust_se(mod_task3_b)),
  omit = c("Education_Level","Age_Range"),
  add.lines = list(c('Education Fixed Effects', 'No','Yes'),
    c('Age Fixed Effects','No','Yes')),
  header=FALSE,
  type='latex')

```

Table 5:

	<i>Dependent variable:</i>	
	TaskPhase3_Score	
	(1)	(2)
Treatment_Dummy	0.004 (0.019)	0.002 (0.019)
TaskPhase1_Score		0.161*** (0.047)
as.factor(Gender)Male		−0.004 (0.017)
Constant	0.538*** (0.017)	0.515*** (0.064)
Education Fixed Effects	No	Yes
Age Fixed Effects	No	Yes
Observations	350	350
R ²	0.0001	0.084
Adjusted R ²	−0.003	0.049
Residual Std. Error	0.160 (df = 348)	0.155 (df = 336)
F Statistic	0.034 (df = 1; 348)	2.384*** (df = 13; 336)

Note:

*p<0.1; **p<0.05; ***p<0.01

```

# test final task and specific treatment
mod_task3_c <- d_respondents[, lm(TaskPhase3_Score ~ as.factor(Assignment_Group))]
mod_task3_d <- d_respondents[, lm(TaskPhase3_Score ~ as.factor(Assignment_Group) +
  TaskPhase1_Score +
  as.factor(Gender) +
  as.factor(Education_Level) +
  as.factor(Age_Range))]

stargazer(mod_task3_c,
  mod_task3_d,
  se = list(get_robust_se(mod_task3_c),get_robust_se(mod_task3_d)),
  omit = c("Education_Level","Age_Range"),
  add.lines = list(c('Education Fixed Effects', 'No','Yes'),
    c('Age Fixed Effects','No','Yes')),

```

```
header=FALSE,
type='latex')
```

Table 6:

	<i>Dependent variable:</i>	
	TaskPhase3_Score	
	(1)	(2)
as.factor(Assignment_Group)Medical Feedback	0.022 (0.026)	0.011 (0.026)
as.factor(Assignment_Group)Negative Images	-0.015 (0.027)	-0.011 (0.026)
as.factor(Assignment_Group)Positive Images	-0.001 (0.025)	0.004 (0.025)
as.factor(Assignment_Group)Self-Reflect	0.010 (0.026)	0.005 (0.026)
TaskPhase1_Score		0.157*** (0.047)
as.factor(Gender)Male		-0.004 (0.017)
Constant	0.538*** (0.017)	0.518*** (0.064)
Education Fixed Effects	No	Yes
Age Fixed Effects	No	Yes
Observations	350	350
R ²	0.006	0.087
Adjusted R ²	-0.005	0.043
Residual Std. Error	0.160 (df = 345)	0.156 (df = 333)
F Statistic	0.545 (df = 4; 345)	1.971** (df = 16; 333)

Note:

*p<0.1; **p<0.05; ***p<0.01

```
pander(anova(mod_task3_b, mod_task3_d, test='F'),style='markdown')
```

Table 7: Analysis of Variance Table

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
336	8.117	NA	NA	NA	NA
333	8.099	3	0.01821	0.2496	0.8616

As a quick overview, we'd now like to assess Phase 3 results. As a reminder, this occurs after the subj

What we see across the board though is that the effects of treatment are severely attenuated over time a

This may be attributed to a number of things. For example, more frequent feedback during this short time

As a conclusion, we see that feedback has immediate positive effects on performance, specifically criti

```
## Power
```

```
```r
power.t.test(delta = .05, sd = .16, sig.level = 0.05, power = 0.8)

##
Two-sample t test power calculation
##
n = 161.7
delta = 0.05
sd = 0.16
sig.level = 0.05
power = 0.8
alternative = two.sided
##
NOTE: n is number in *each* group
d_respondents[, .N, by = .(Assignment_Group)]
```

```
Assignment_Group N
1: Negative Images 72
2: Positive Images 70
3: Self-Reflect 69
4: Control 69
5: Medical Feedback 70
```

Power analysis shows that our groups did not have a large enough sample size required for each group. Due to the small effect size of approximately 0.05 when comparing mean TaskPhase2 scores in treatment and control groups, for such small effects to be detected with statistical power of 80%, the number of subjects required in each group would be 162. Our group sizes for the control group, as well as the medical, positive, negative, and self-reflect treatment groups were 69, 70, 70, 72, and 69 respectively. This is primarily due to the fact that we charged too high of a price point per completed survey.

## Conclusions

Our study found a statistically and practically significant impact of several styles of feedback as it relates to performance scores on the X-Ray lung health analysis. We can reject the null hypothesis that the scores in the feedback groups were the same as the scores in the placebo group. Breaking this down further, we see that ***GO INTO THE INDIVIDUAL TREATMENT ATEs***

This experiment faces potential limitations when making more generalized conclusions about the effects of feedback on performance in addition to lower power. For example, the experiment required analysis of a more simple, X-Ray analysis, which is not as complex of a task when compared to writing a paper or performing more quantitative analysis. Furthermore, the experiment's computer-facing setting may have impacted results. Subjects may not have spent as much time on the task as in a real scenario. They certainly did not experiment the same time or social pressures or distractions usually present in most constructive feedback instances

However, the study's conclusions gives us confidence that feedback positively affects performance in a



meaningful way and more specifically targeted, informative feedback drives success. The effects of feedback on performance are significant and merit additional study.

## Limitations and Future Enhancements

The research design generated an output with limited power due to several factors. First, we handicapped the total amount of participants by offering too high of a price point for the survey. Our experiment offered a \$1 price point per successful entry (limit of one entry per person). However we should have charged ~\$0.25. ***DO WE INCLUDE THIS? We also randomized our subjects equally between the four treatment groups and the one control group. In retrospect our group needed to allocate 50% of the participants to the control group and randomly assigned the rest in equal proportions to the four different treatment groups.*** These changes would have given the experiment an estimated 1400 participants, with XYZ in the control group and XYZ split evenly between the different treatment groups. Power for the experiment would have increased substantially and allowed for more meaningful outcomes.