Mediation

- explains how or why an intervention works
- mediator explains all or part of the treatment's impact on an intended outcome
- is an intermediate outcome that is measured or observed after the onset of the intervention. E.g. fidelity of application, how many questions were asked ?

Moderation

- explains who the intervention benefits or what conditions must exist for the intervention to be effective.
- a factor that reflects who is most affected by the treatment
- a factor that exists prior to the introduction of an intervention Eg. student characteristics, such as special education status, gender, ...

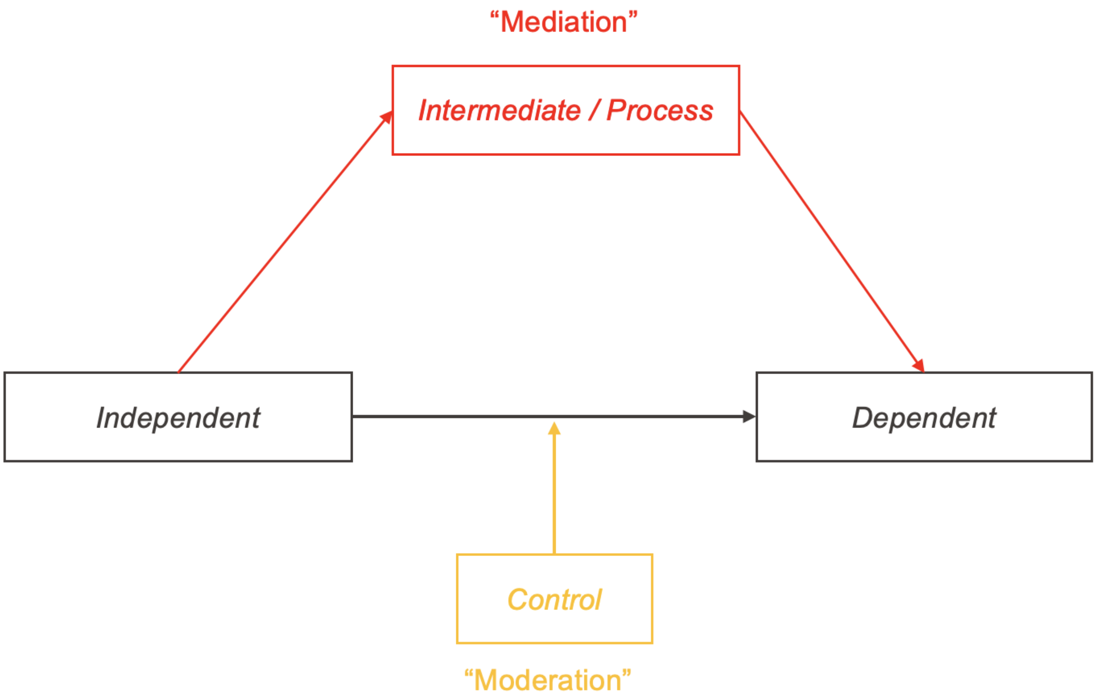


Figure 1: Overview

Dataset

This dataset was generated to illustrate basic statistical techniques like ANOVA and regression as well lightly more advanced techniques like mediation and moderation. However, we tried as much as possible to implement variations compatible with insights found in the literature about Productive Failure:

Sinha, T., & Kapur, M. (2021). When Problem Solving Followed by Instruction Works: Evidence for Productive Failure. Review of Educational Research, 91(5), 761–798. https://doi.org/10.3102/00346543211019105

Participants

The sample consisted of N=200 participants.

Independent variable

Order of instruction The independent variable has two modalities (also called conditions):

- I-PS : instruction followed by problem-solving
- PS-I : problem-solving followed by instruction

Participants were *randomly* assigned to one of the experimental conditions.

Dependent variable

Learning gain. Participants completed a 10 question *pre-test* before starting the experiment. The pre-test was a series of questions about their understanding of the sun-earth relative positions. After the experiment, particpants completed a 10 question *post-test* with similar questions as the pre-test. The learning gain was computed as :

$learning.gain = post.test - pre.test$

another possibilty would be the relative learning gain

$rel.gain = \frac{post.test - pre.test}{max - pre.test}$

Control variables

Age group. Participants were recruited among highschool students who are interested in following studies at EPFL (kids), students doing their bachelor as well as alumni who are active professionally (professionals).

Young learners (e.g., second to fifth graders) may have insufficient prior knowledge about cognitive and metacognitive learning strategies to generate multiple solutions during initial problem solving

Gender. Experimenters also asked for the gender of the participants, either Male (M) or Female (M).

Self-regulation skills. Participants also filled in a questionnaire about their self.regulation skills by using the Learning Companion (https://companion.epfl.ch)

Intermediate / Process variables

Solutions. The simulation system logged every simulation run and counted how often students used the simulation to generate a potential solution.

Mediation

- explains how or why an intervention works
- mediator explains all or part of the treatment's impact on an intended outcome
- is an intermediate outcome that is measured or observed **after** the onset of the intervention. E.g. fidelity of application, how many questions were asked ?
- there is a plausible causality relation between the experimental treatment and the mediating variable.

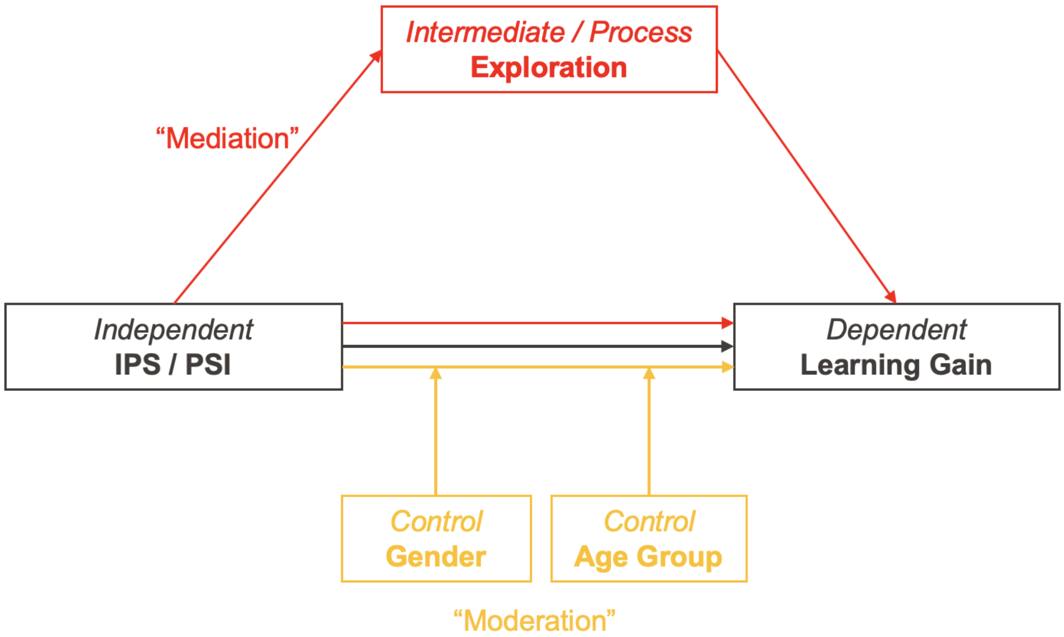


Figure 5: Overview

The “old” way

Baron and Kenny’s (1986) steps for mediation analysis See https://davidakenny.net/cm/mediate.htm

> Step 1: Show that the causal variable is correlated with the outcome. Use Y as the criterion variable in a regression equation and X as a predictor (estimate and test path c in the above figure). This step establishes that there is an effect that may be mediated.
>
> Step 2: Show that the causal variable is correlated with the mediator. Use M as the criterion variable in the regression equation and X as a predictor (estimate and test path a). This step essentially involves treating the mediator as if it were an outcome variable.
>
> Step 3: Show that the mediator affects the outcome variable. Use Y as the criterion variable in a regression equation and X and M as predictors (estimate and test path b). It is not sufficient just to correlate the mediator with the outcome because the mediator and the outcome may be correlated because they are both caused by the causal variable X. Thus, the causal variable must be controlled in establishing the effect of the mediator on the outcome.
>
> Step 4: To establish that M completely mediates the X-Y relationship, the effect of X on Y controlling for M (path c’) should be zero (see discussion below on significance testing). The effects in both Steps 3 and 4 are estimated in the same equation.

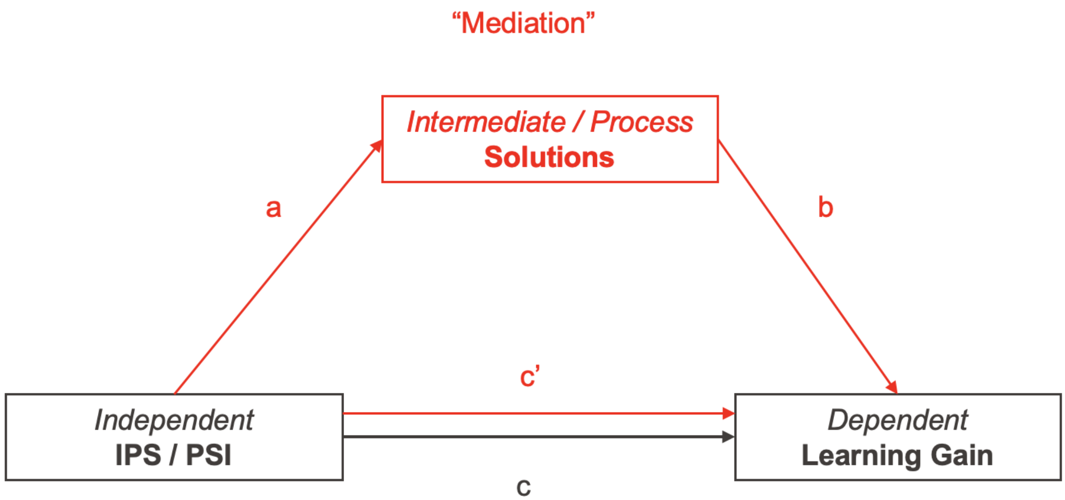
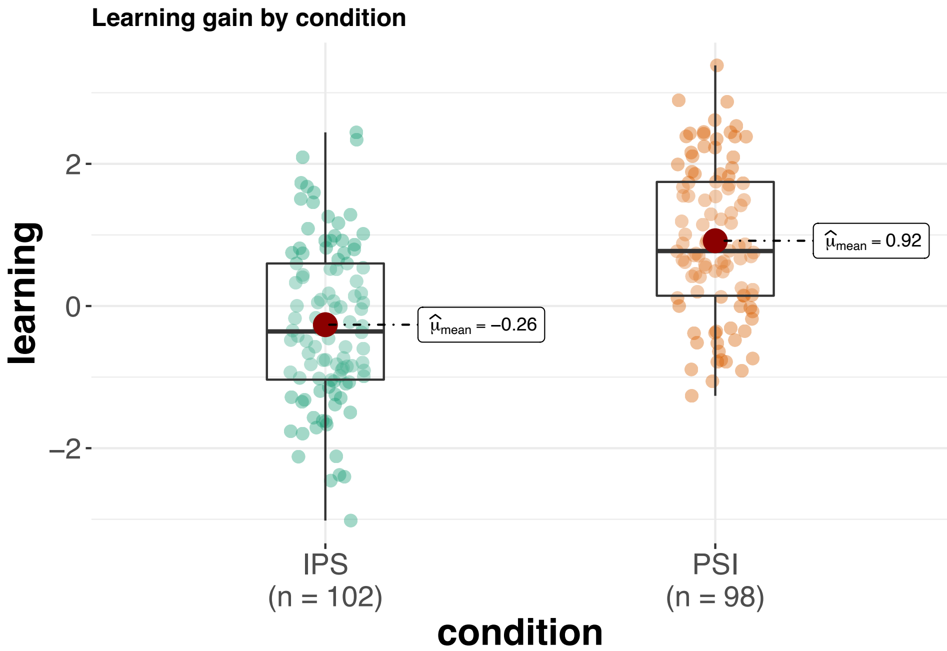


Figure 7: Mediation

Condition affects the learning gain (c path)



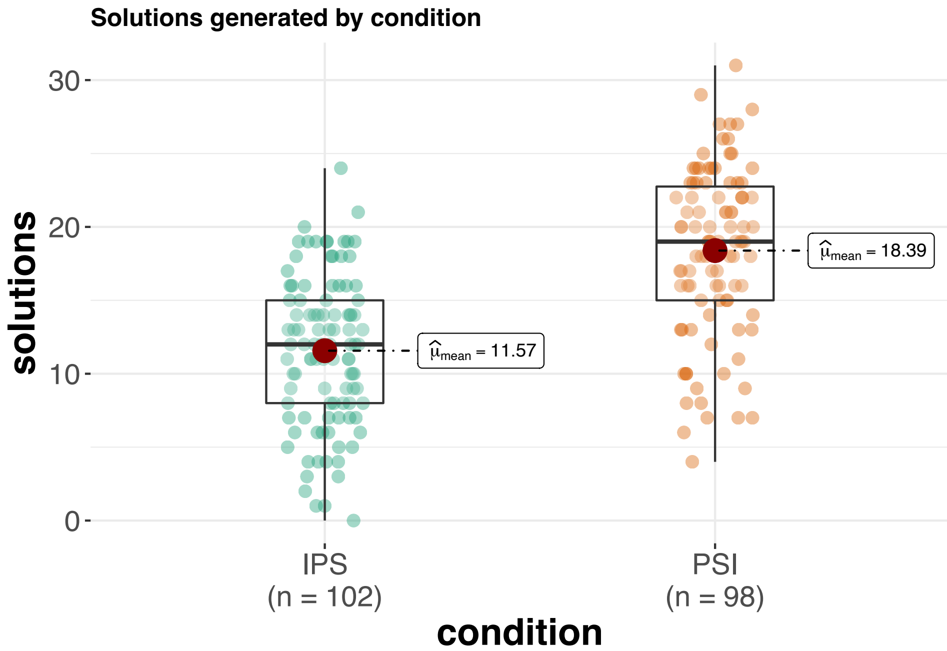
Step 1

First we make sure the experimental treatment affects the dependent variable.

```r
c.path <- lm(learning ~ condition, data=df)
summary(c.path)
```

```
##
## Call:
## lm(formula = learning ~ condition, data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.7555 -0.7754 -0.1243  0.8605  2.7054
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -0.2626     0.1092  -2.405   0.0171 *
## conditionPSI  1.1806     0.1560   7.567 1.41e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.103 on 198 degrees of freedom
## Multiple R-squared:  0.2243, Adjusted R-squared:  0.2204
## F-statistic: 57.26 on 1 and 198 DF,  p-value: 1.412e-12
```

Condition affects the number of solutions generated (a path)



Step 2

This model checks whether the experimental treatment affects the mediating variable

```
a.path <- lm(solutions ~ condition, data=df)
summary(a.path)
```

```
##
## Call:
## lm(formula = solutions ~ condition, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -14.3878  -3.5686   0.5218   3.6122  12.6122
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  11.5686     0.5344  21.647  < 2e-16 ***
## conditionPSI   6.8191     0.7635   8.932  2.9e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.397 on 198 degrees of freedom
## Multiple R-squared:  0.2872, Adjusted R-squared:  0.2836
## F-statistic: 79.78 on 1 and 198 DF,  p-value: 2.903e-16
```

Step 3 & 4

Finally we check whether:

- the mediating variable affects the dependent variable and
- that the effect of the independent variable **decreases** (partial mediation) or even **dissapears** (full mediation).

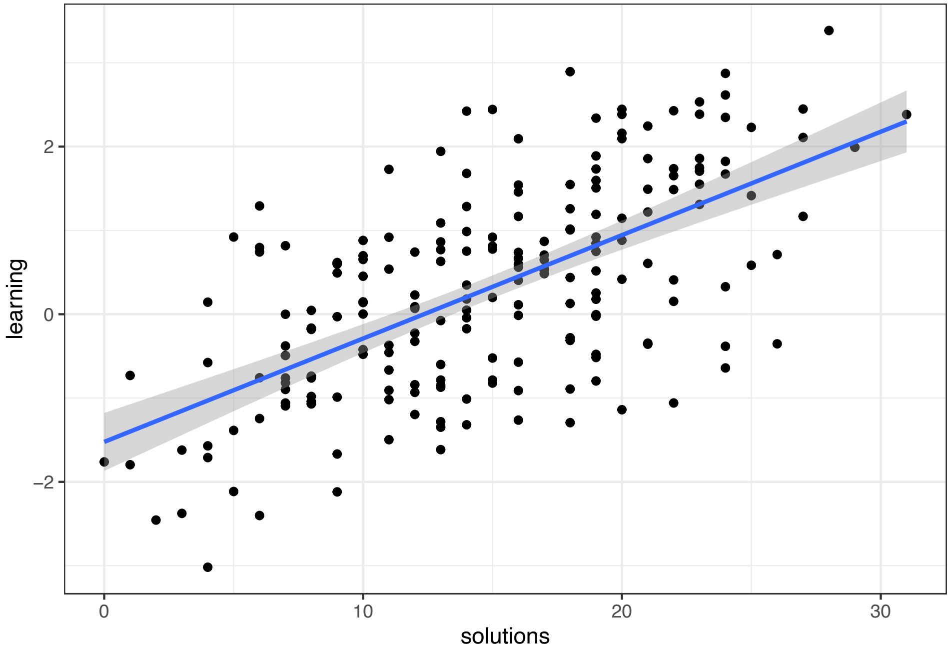
In our case:

- the Estimate for the mediator (solutions) is statistically significant and

- the Estimate for conditionPSI went down from 1.1806 to 0.4764, but is still significant => we have a partial mediation

Solutions and Learning gain are correlated (b path)

```
## [1] 0.6295641
```



```r
c.dash.path <- lm(learning  ~ condition + solutions, data=df)
summary(c.dash.path)
```

```
##
## Call:
## lm(formula = learning ~ condition + solutions, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.34975 -0.64637 -0.00054  0.65168  2.35102
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -1.45730    0.17336  -8.406 8.41e-15 ***
## conditionPSI  0.47639    0.15987   2.980  0.00325 **
## solutions     0.10327    0.01256   8.219 2.70e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9542 on 197 degrees of freedom
## Multiple R-squared:  0.4224, Adjusted R-squared:  0.4165
## F-statistic: 72.03 on 2 and 197 DF,  p-value: < 2.2e-16
```

Mediation - Sobel test.

Sobel has developped a method to test whether this mediation effect is significant. See http://www.quantpsy.org/sobel/sobel.htm

$z - value = \frac{a*b}{\sqrt{b^2*S_a^2+a^2+S_b^2}}$

where :

- a is the unstandardised Coefficient of the independent variable
- S_a is the standard error of the independent variable
- b is the unstandardised Coefficient of the mediation variable
- S_b is the standard error of the mediation variable

Downsides, the distribution of a*b is only normal for large samples, therefore people use a bootstrap method to estimate the confidence interval of ab. If it comprises 0 it is not significant, else it is.

```r
# a path
coef(summary(a.path))
```

```
##                Estimate Std. Error   t value     Pr(>|t|)
## (Intercept)  11.568627  0.5344298 21.646673 4.337682e-54
## conditionPSI  6.819128  0.7634712  8.931742 2.902753e-16
```

```r
# a is the unstandardised coefficient for the path from X to M
a = 6.819128
Sa = 0.7634712

# c_dash path
coef(summary(c.dash.path))
```

```
##                Estimate Std. Error   t value     Pr(>|t|)
## (Intercept)  -1.4573040 0.17336240 -8.406113 8.413584e-15
## conditionPSI  0.4763879 0.15987428  2.979766 3.247729e-03
## solutions     0.1032689 0.01256431  8.219223 2.700434e-14
```

```r
# b refers to the unstadardised coefficient for the path from M to Y
b=0.1032689
Sb=0.01256431
```

```r
# Average Causal Mediation Effect (ACME)
acme <- a*b
acme
```

```
## [1] 0.7042038
```

```r
# Sobel's Z
z <- (a*b) / sqrt(b^2 * Sa^2 + b^2 * Sa^2)
z
```

```
## [1] 6.315696
```

Doing the z-test

We now determine whether this mediation effect is statistically significant (not due to sampling error) with a two-tailed z-test of the hypothesis that the mediated effect equals zero in the population.

H_0: the mediation effect is zero

H_1: the mediation effect is not zero

```
# The critical value (1.96 for a two tailed test with alpha = 0.05)
critical.value <- qnorm(0.025, mean = 0, sd = 1, lower.tail = FALSE)
critical.value
```

```
## [1] 1.959964
```

The z-value we obtained (6.33) is much higher than the critical value of 1.96.

We can compute the p-value associated with it. Since it is much lower than alpha (0.05) we can reject H_0 and conclude that the mediation effect is significant.

```
p.value <- pnorm(q = z, mean = 0, sd = 1, lower.tail = FALSE)
p.value
```

```
## [1] 1.344745e-10
```

Estimating the proportion of mediation with the mediation package

To alleviate the downsides of the z test (not normally distributed for small samples), we can use a bootstrapping method and simulate 1000 samples to estimage the confidence intervals for the indirect and direct effects.

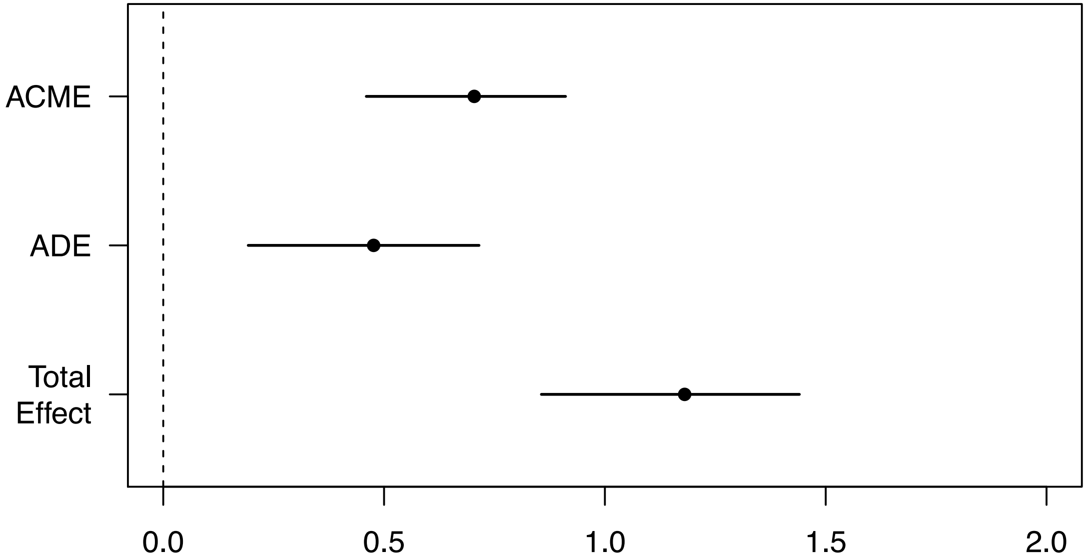
```
library(mediation) # Gives mediate()

results <- mediate(a.path, c.dash.path,
                   treat='condition',
                   mediator='solutions',
                   boot=TRUE, sims=100,
                   control.value = "IPS",
                   treat.value = "PSI")
```

The direct effect (c path) is listed as ADE (average direct effect), the mediation path (ab path) is listed as ACME (average causal mediation effects, ACME). The total effect is ACE + ACME.

```
summary(results)
```

```
##
## Causal Mediation Analysis
##
## Nonparametric Bootstrap Confidence Intervals with the Percentile Method
##
##                Estimate 95% CI Lower 95% CI Upper p-value
## ACME              0.704        0.460         0.91  <2e-16 ***
## ADE               0.476        0.192         0.72    0.02 *
## Total Effect      1.181        0.856         1.44  <2e-16 ***
## Prop. Mediated    0.596        0.423         0.83  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sample Size Used: 200
##
##
## Simulations: 100
```


ACME
ADE
Total Effect
0.0
0.5
1.0
1.5
2.0

Moderated mediation

Remember we found out in the previous ANOVA analyses that the age group was a moderator for the effect of the experimental treatment.

We now look into whether the mediation is also moderated by this variable.

Model c

Predicting the dependent variable with the condition

NB: this was our model.2 when doing 2-factor ANOVA earlier. In this context we use the default contrasts ("treatment") when building the lm model.

```
model.c <- lm(learning ~ condition + age.group + condition:age.group, data=df)
coef(summary(model.c))
```

```
##                                     Estimate Std. Error   t value
## (Intercept)                       -0.6108569  0.1802479 -3.388983
## conditionPSI                       1.1814799  0.2731392  4.325559
## age.groupstudents                  0.2800331  0.2549090  1.098561
## age.groupprofessionals             0.8037029  0.2608150  3.081506
## conditionPSI:age.groupstudents     0.4406413  0.3701604  1.190406
## conditionPSI:age.groupprofessionals -0.6020656  0.3802612 -1.583295
##                                         Pr(>|t|)
## (Intercept)                       8.496561e-04
## conditionPSI                      2.432415e-05
## age.groupstudents                 2.733210e-01
## age.groupprofessionals            2.359029e-03
## conditionPSI:age.groupstudents    2.353413e-01
## conditionPSI:age.groupprofessionals 1.149831e-01
```

Model a

Predicting the mediator variable with the condition

```r
model.a <- lm(solutions ~ condition + age.group + condition:age.group, data=df)
coef(summary(model.a))
```

```
##                                        Estimate Std. Error   t value     Pr(>|t|)
## (Intercept)                            8.428571  0.6949723 12.127925 1.466060e-25
## conditionPSI                           3.164021  1.0531287  3.004401 3.012129e-03
## age.groupstudents                      2.971429  0.9828392  3.023311 2.838132e-03
## age.groupprofessionals                 6.758929  1.0056107  6.721218 1.957578e-10
## conditionPSI:age.groupstudents         6.593874  1.4272079  4.620121 6.978416e-06
## conditionPSI:age.groupprofessionals 2.406055  1.4661531  1.641066 1.024039e-01
```

Model c.dash

Same as model c but we add the mediator (solutions).

```
model.c.dash <- lm(learning ~ condition + age.group + condition:age.group +
                solutions,
                data=df)
coef(summary(model.c.dash))
```

```
##                                     Estimate Std. Error    t value
## (Intercept)                      -1.67136590 0.20953421 -7.9765777
## conditionPSI                      0.78337292 0.24496999  3.1978322
## age.groupstudents                -0.09384122 0.22868401 -0.4103532
## age.groupprofessionals           -0.04672643 0.25388833 -0.1840432
## solutions                         0.12582310 0.01632507  7.7073524
## conditionPSI:age.groupstudents   -0.38902032 0.34190884 -1.1377896
## conditionPSI:age.groupprofessionals -0.90480279 0.33568276 -2.6954104
##                                     Pr(>|t|)
## (Intercept)                      1.299331e-13
## conditionPSI                     1.618355e-03
## age.groupstudents                6.820020e-01
## age.groupprofessionals           8.541728e-01
## solutions                        6.605332e-13
## conditionPSI:age.groupstudents   2.566188e-01
## conditionPSI:age.groupprofessionals 7.650840e-03
```

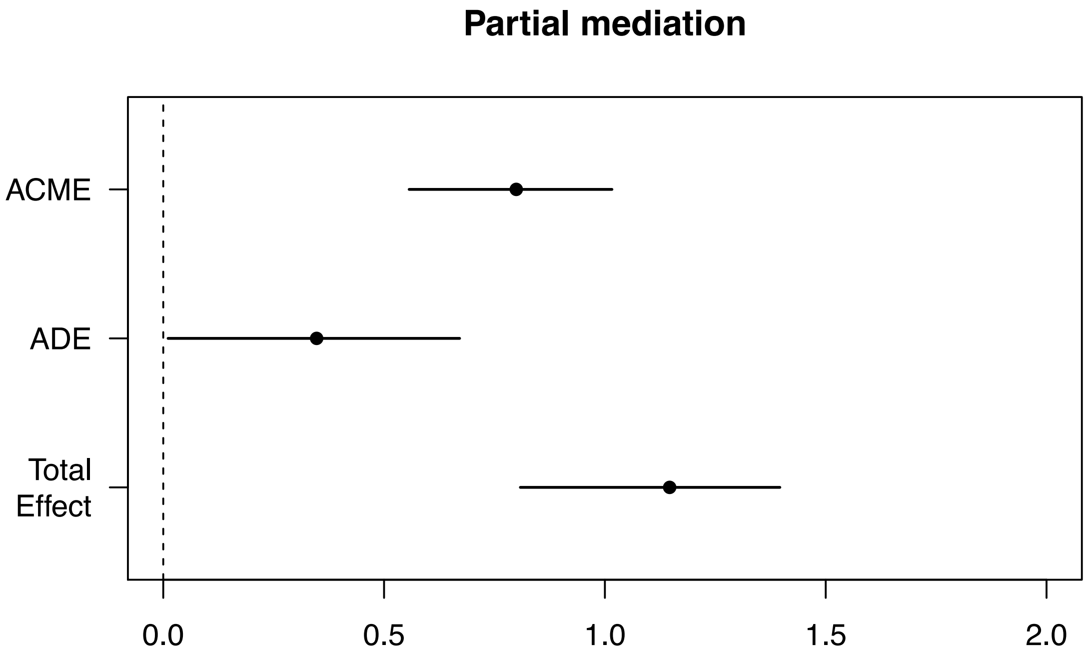
With mediate() package

```
results <- mediate(model.a, # predicts mediator with condition
                   model.c.dash, # predicts learning with condition and solutions
                   treat='condition',
                   mediator='solutions',
                   boot=TRUE, sims=100, # run bootstrapping procedure
                   control.value = "IPS",
                   treat.value = "PSI")
```

The results indicate a **partial** mediation (ACME **and** ADE are significant).

```
summary(results)
```

```
## 
## Causal Mediation Analysis
## 
## Nonparametric Bootstrap Confidence Intervals with the Percentile Method
## 
##                Estimate 95% CI Lower 95% CI Upper p-value    
## ACME             0.7993       0.5568         1.02  <2e-16 ***
## ADE              0.3473       0.0109         0.67    0.04 *  
## Total Effect     1.1466       0.8086         1.40  <2e-16 ***
## Prop. Mediated   0.6971       0.4935         0.99  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Sample Size Used: 200 
## 
## 
## Simulations: 100
```

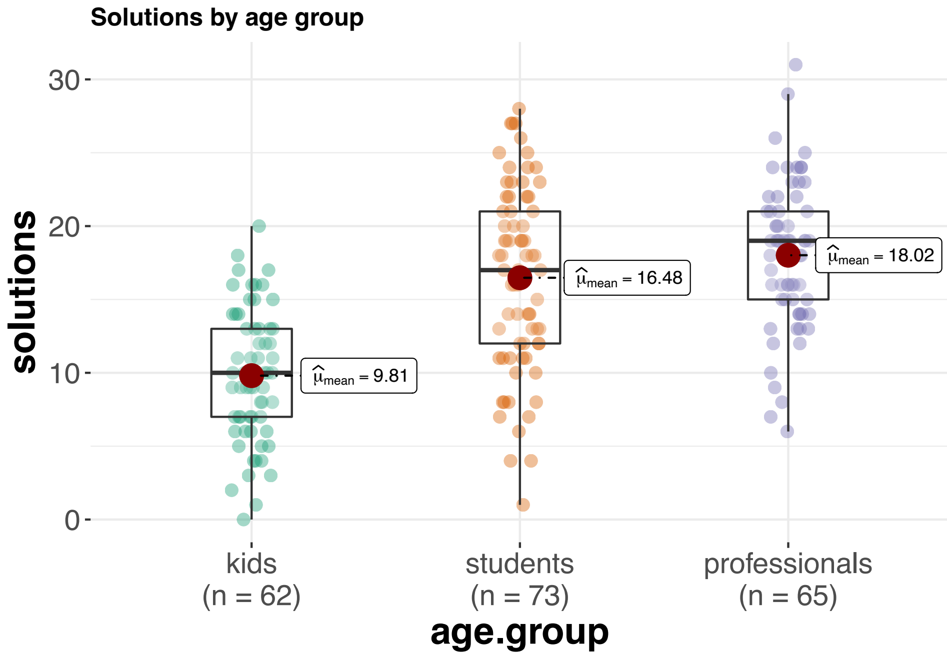

Partial mediation
ACME
ADE
Total
Effect
0.0
0.5
1.0
1.5
2.0

Moderated mediation with age group

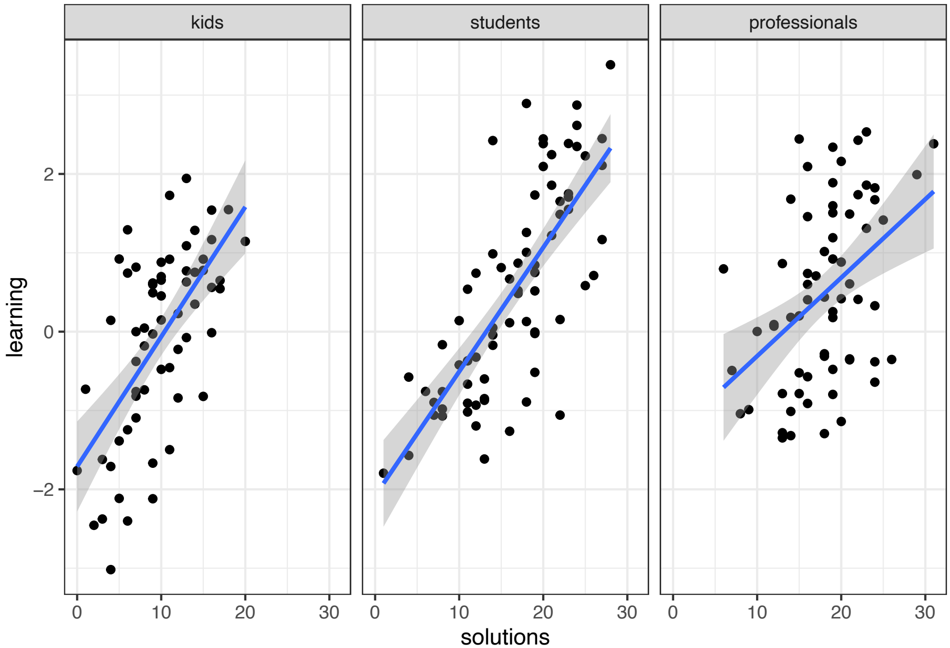
- It appears that kids have created less solutions than students and professionals.
- It appears that the relation between solutions and learning is different for different age groups.

Does the mediation exist for all age groups ?

kids have created less solutions than students and professionals



the relation between solutions and learning is different for different age groups



Adding covariates to the `mediate()` function

Approach: We compute the mediation for each age subgroup. This is done by adding a covariates argument to the mediate function.

```
results.kids <- mediate(model.a, model.c.dash, treat='condition', mediator='solutions', boot=TRUE,sims=
                   covariates = list(age.group="kids"))
summary(results.kids)
```

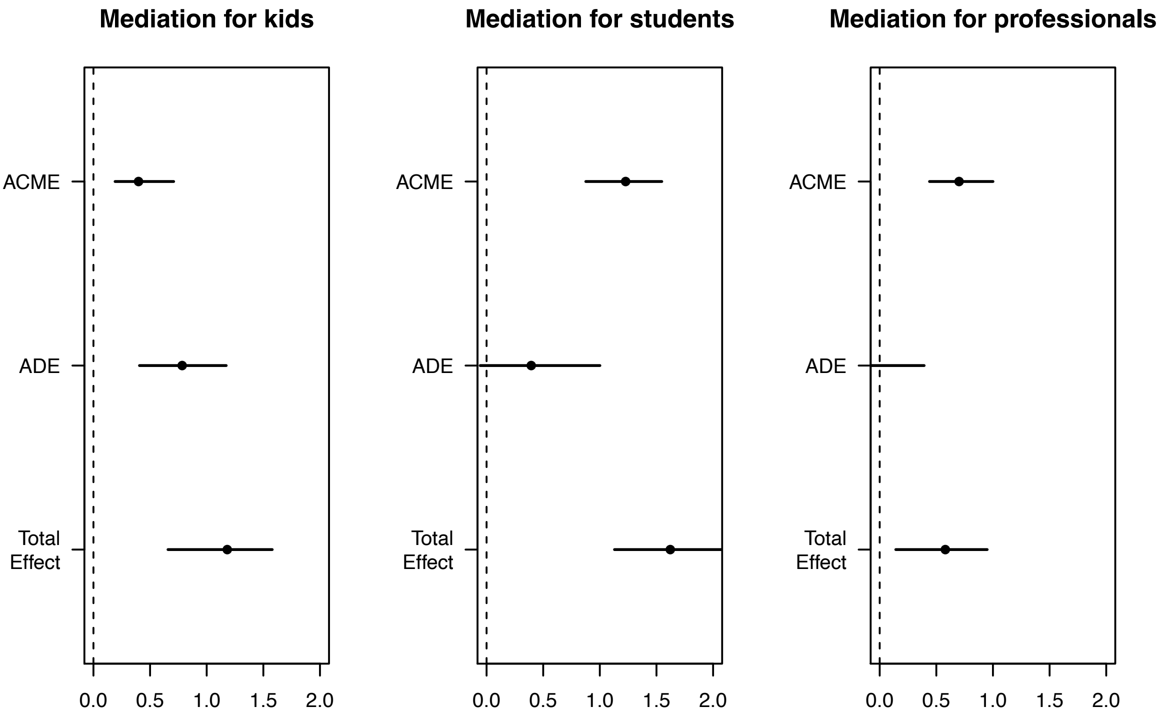
```
##
## Causal Mediation Analysis
##
## Nonparametric Bootstrap Confidence Intervals with the Percentile Method
##
## (Inference Conditional on the Covariate Values Specified in `covariates')
##
##                 Estimate 95% CI Lower 95% CI Upper p-value
## ACME               0.398        0.191         0.71  <2e-16 ***
## ADE                0.783        0.406         1.17  <2e-16 ***
## Total Effect       1.181        0.658         1.58  <2e-16 ***
## Prop. Mediated     0.337        0.177         0.55  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sample Size Used: 200
##
##
## Simulations: 100
```

```r
results.students <-mediate(model.a, model.c.dash, treat='condition', mediator='solutions', boot=TRUE,si
                    covariates = list(age.group="students"))
summary(results.students)
```

```
##
## Causal Mediation Analysis
##
## Nonparametric Bootstrap Confidence Intervals with the Percentile Method
##
## (Inference Conditional on the Covariate Values Specified in `covariates')
##
##                Estimate 95% CI Lower 95% CI Upper p-value
## ACME             1.2278       0.8760         1.55  <2e-16 ***
## ADE              0.3944      -0.0568         1.00    0.12
## Total Effect     1.6221       1.1293         2.09  <2e-16 ***
## Prop. Mediated   0.7569       0.5137         1.05  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sample Size Used: 200
##
##
## Simulations: 100
```

```r
results.professionals <- mediate(model.a, model.c.dash, treat='condition', mediator='solutions', boot=T
                         covariates = list(age.group="professionals"))
summary(results.professionals)
```

```
##
## Causal Mediation Analysis
##
## Nonparametric Bootstrap Confidence Intervals with the Percentile Method
##
## (Inference Conditional on the Covariate Values Specified in `covariates')
##
##                Estimate 95% CI Lower 95% CI Upper p-value
## ACME              0.701        0.440         1.00  <2e-16 ***
## ADE              -0.121       -0.601         0.39    0.74
## Total Effect      0.579        0.142         0.95  <2e-16 ***
## Prop. Mediated    1.210        0.562         4.56  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sample Size Used: 200
##
##
## Simulations: 100
```


Mediation for kids
Mediation for students
Mediation for professionals
ACME
ADE
Total Effect
0.0
0.5
1.0
1.5
2.0

Pushing the envelope ...

Testing whether the direct and indirect effects are different across groups ?

```
test.modmed(results,
            covariates.1 = list(age.group = "kids"),
            covariates.2 = list(age.group = "students"), sims = 100)
```

```
##
##  Test of ACME(covariates.1) - ACME(covariates.2) = 0
##
## data:  estimates from results
## ACME(covariates.1) - ACME(covariates.2) = -0.82966, p-value < 2.2e-16
## alternative hypothesis: true ACME(covariates.1) - ACME(covariates.2) is not equal to 0
## 95 percent confidence interval:
##  -1.330910 -0.344623
##
##
##  Test of ADE(covariates.1) - ADE(covariates.2) = 0
##
## data:  estimates from results
## ADE(covariates.1) - ADE(covariates.2) = 0.38902, p-value = 0.34
## alternative hypothesis: true ADE(covariates.1) - ADE(covariates.2) is not equal to 0
## 95 percent confidence interval:
##  -0.160029  1.071236
```

```r
test.modmed(results,
            covariates.1 = list(age.group = "kids"),
            covariates.2 = list(age.group = "professionals"), sims = 100)
```

```
##
##  Test of ACME(covariates.1) - ACME(covariates.2) = 0
##
## data:  estimates from results
## ACME(covariates.1) - ACME(covariates.2) = -0.30274, p-value = 0.1
## alternative hypothesis: true ACME(covariates.1) - ACME(covariates.2) is not equal to 0
## 95 percent confidence interval:
##  -0.71011597  0.02555824
##
##
##  Test of ADE(covariates.1) - ADE(covariates.2) = 0
##
## data:  estimates from results
## ADE(covariates.1) - ADE(covariates.2) = 0.9048, p-value < 2.2e-16
## alternative hypothesis: true ADE(covariates.1) - ADE(covariates.2) is not equal to 0
## 95 percent confidence interval:
##  0.3385389 1.7701618
```

```r
test.modmed(results,
            covariates.1 = list(age.group = "students"),
            covariates.2 = list(age.group = "professionals"), sims = 100)
```

```
##
##  Test of ACME(covariates.1) - ACME(covariates.2) = 0
##
## data:  estimates from results
## ACME(covariates.1) - ACME(covariates.2) = 0.52692, p-value = 0.04
## alternative hypothesis: true ACME(covariates.1) - ACME(covariates.2) is not equal to 0
## 95 percent confidence interval:
##  0.05270736 1.07853506
##
##
##  Test of ADE(covariates.1) - ADE(covariates.2) = 0
##
## data:  estimates from results
## ADE(covariates.1) - ADE(covariates.2) = 0.51578, p-value = 0.1
## alternative hypothesis: true ADE(covariates.1) - ADE(covariates.2) is not equal to 0
## 95 percent confidence interval:
##  -0.1256427  1.2747345
```

Role of a pre-treatment moderator ?

We now look at the potential influence of a potential pre-treatment moderator, the `self.regulation` skills of the participants.

We wonder whether the potential positive effect of testing many solutions is conditioned on the level of self-regulation skills.

The rationale for this could be: when you run experiments (generate many `solutions`), you learn more if you can accurately revise your hypotheses (`self-regulation`) about the phenomenon. This would mean that the moderation effect that we discovered for the number of solutions would be present mainly for subjects with a high level of self-regulation skills.

The analysis we conduct is similar to the one we did for `age.group` except that this time, the moderator is a continuous variable.

```
model.a2 <- lm(solutions ~ condition + self.regulation +
                 condition:self.regulation, data=df)

model.c2.dash <- lm(learning ~ condition + self.regulation +
                      condition:self.regulation +
                      solutions, data=df)
```

```r
results.self.regulation <- mediate(model.a2, model.c2.dash, treat='condition', mediator='solutions',
                                    boot=TRUE,sims=100, control.value = "IPS", treat.value = "PSI")
summary(results.self.regulation)
```

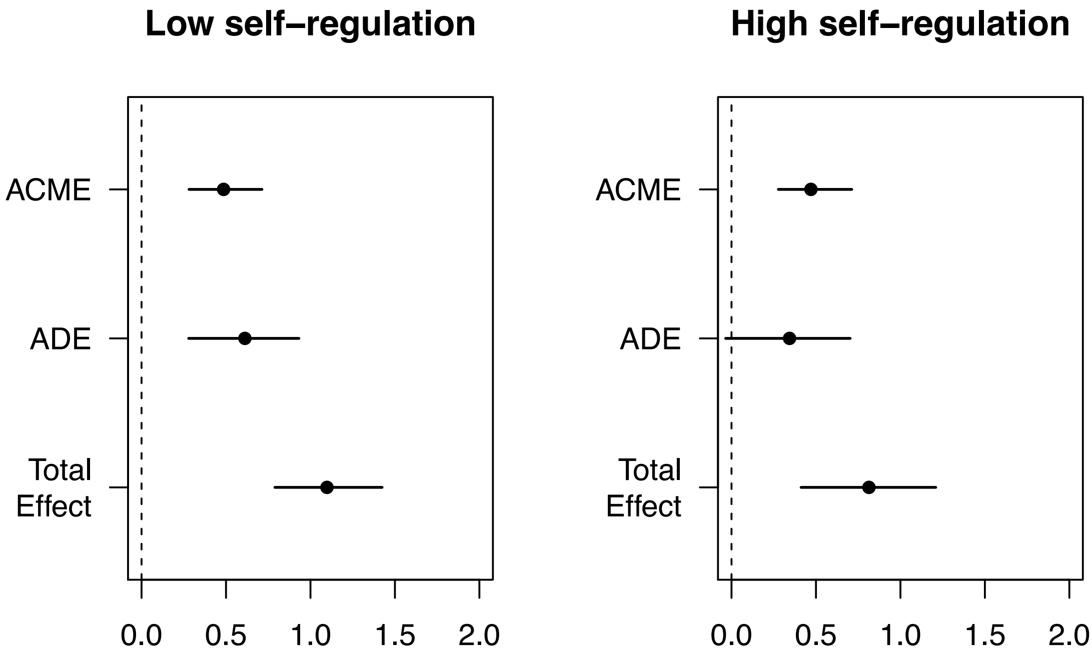
```
##
## Causal Mediation Analysis
##
## Nonparametric Bootstrap Confidence Intervals with the Percentile Method
##
##                Estimate 95% CI Lower 95% CI Upper p-value
## ACME              0.478        0.286         0.70  <2e-16 ***
## ADE               0.473        0.226         0.79  <2e-16 ***
## Total Effect      0.950        0.699         1.22  <2e-16 ***
## Prop. Mediated    0.503        0.336         0.71  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sample Size Used: 200
##
##
## Simulations: 100
```

```r
results.hi.self.regulation <- mediate(model.a2, model.c2.dash, treat='condition', mediator='solutions',
                                      boot=TRUE,sims=500, control.value = "IPS", treat.value = "PSI",
                   covariates = list(self.regulation=quantile(df$self.regulation, .75)))
summary(results.hi.self.regulation)
```

```
##
## Causal Mediation Analysis
##
## Nonparametric Bootstrap Confidence Intervals with the Percentile Method
##
## (Inference Conditional on the Covariate Values Specified in `covariates')
##
##                  Estimate 95% CI Lower 95% CI Upper p-value
## ACME               0.4700       0.2772         0.71  <2e-16 ***
## ADE                0.3437      -0.0347         0.70   0.088 .
## Total Effect       0.8137       0.4119         1.21  <2e-16 ***
## Prop. Mediated     0.5776       0.3458         1.07  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sample Size Used: 200
##
##
## Simulations: 500
```

```r
results.lo.self.regulation <- mediate(model.a2, model.c2.dash, treat='condition', mediator='solutions',
                                      boot=TRUE,sims=500, control.value = "IPS", treat.value = "PSI",
                   covariates = list(self.regulation=quantile(df$self.regulation, .25)))
summary(results.lo.self.regulation)
```

```
##
## Causal Mediation Analysis
##
## Nonparametric Bootstrap Confidence Intervals with the Percentile Method
##
## (Inference Conditional on the Covariate Values Specified in `covariates')
##
##                  Estimate 95% CI Lower 95% CI Upper p-value
## ACME                0.486        0.281         0.71  <2e-16 ***
## ADE                 0.612        0.279         0.93  <2e-16 ***
## Total Effect        1.098        0.790         1.42  <2e-16 ***
## Prop. Mediated      0.443        0.271         0.68  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sample Size Used: 200
##
##
## Simulations: 500
```


Low self−regulation
High self−regulation
ACME
ADE
Total
Effect
0.0
0.5
1.0
1.5
2.0

We finally test whether the mediation and direct effects are different for sutdentd with hi and lo self regulation skills

```
test.modmed(results.self.regulation,
            covariates.1 = list(self.regulation=quantile(df$self.regulation, .25)),
            covariates.2 = list(self.regulation=quantile(df$self.regulation, .75)), sims = 500)
```

```
##
##  Test of ACME(covariates.1) - ACME(covariates.2) = 0
##
## data:  estimates from results.self.regulation
## ACME(covariates.1) - ACME(covariates.2) = 0.015756, p-value = 0.88
## alternative hypothesis: true ACME(covariates.1) - ACME(covariates.2) is not equal to 0
## 95 percent confidence interval:
##  -0.3241569  0.3702842
##
##
##  Test of ADE(covariates.1) - ADE(covariates.2) = 0
##
## data:  estimates from results.self.regulation
## ADE(covariates.1) - ADE(covariates.2) = 0.26823, p-value = 0.304
## alternative hypothesis: true ADE(covariates.1) - ADE(covariates.2) is not equal to 0
## 95 percent confidence interval:
##  -0.2742372  0.7459550
```