Moderation Designs

DClin Research Methods 1

Dr Christopher Wilson
Teesside University

Recap

- Thinking about more than outcomes. Designing studies to answer more **specific research questions / think about process**.
  - "Why is this happening?"
  - "What is the mechanism?"
- Thinking beyond significance testing. Using **confidence intervals and effect sizes** to interpret results.
  - "How big is the effect?"
  - "What is the range of plausible values?"
- Thinking about the relationship between variables. Modelling relationships between variables using regression.
  - "Does **Predictor Variable** (e.g. Treatment Group, Avoidance, Trait) predict **Outcome Variable** (e.g. Wellbeing, Depression, Behaviour)?"
  - "How much variance is explained by the model?"

Last week and the week before

- Thinking about the relationship between variables. Modelling relationships between variables using regression.
  - “Does **Predictor Variable** (e.g. Treatment Group, Avoidance, Trait) predict **Outcome Variable** (e.g. Wellbeing, Depression, Behaviour)?”
  - “How much variance is explained by the model?”

- We looked at building regression models based on our research questions and hypotheses.
- This allowed us to consider the contribution of multiple predictors to an outcome variable.

Today

> - Thinking about more than outcomes. Designing studies to answer more **specific research questions / think about process**.
>   - “Why is this happening?”
>   - “What is the mechanism?”

- We will be looking at how we can use regression to model **interactions** between variables.
- We will also be looking at how we can use regression to model **moderation** of relationships between variables.

What are interactions? #1

- Interactions are when the outcome variable is influenced by the interaction between two or more predictor variables.

For example, if we are looking at whether *Time in counselling* and *Rapport level with clinician* predict *General Wellbeing*.

- Without the interaction, we consider the effect of *Time in counselling* or *Rapport level with clinician* on *General Wellbeing*.
- With the interaction, we consider the effect of *Time in counselling* on *General Wellbeing* at different levels of *Rapport level with clinician* (or vice versa).

Note: All assumptions of multiple regression also apply to interactions and moderation.

How do we check for interactions?

- We can check if there is an interaction between predictor variables when we build our regression model.
- We do this by adding a term to our model that represents the interaction between the predictor variables.

```
# model1 without interactions

model1 <- lm(data = modData, generalWellbeing ~ timeInCounselling + rapportLevel)

# model1 with interactions

model1 <- lm(data = modData, generalWellbeing ~ timeInCounselling * rapportLevel)
```

① This model does not include an interaction between timeInCounselling and rapportLevel. This is because we used the + symbol to separate the predictor variables.

② This model does include an interaction between timeInCounselling and rapportLevel. This is because we used the * symbol to separate the predictor variables.

Interpreting interactions in regression #1

```r
# model1 with interactions

model1 <- lm(data = modData, generalWellbeing ~ timeInCounselling * rapportLevel)

summary(model1)
```

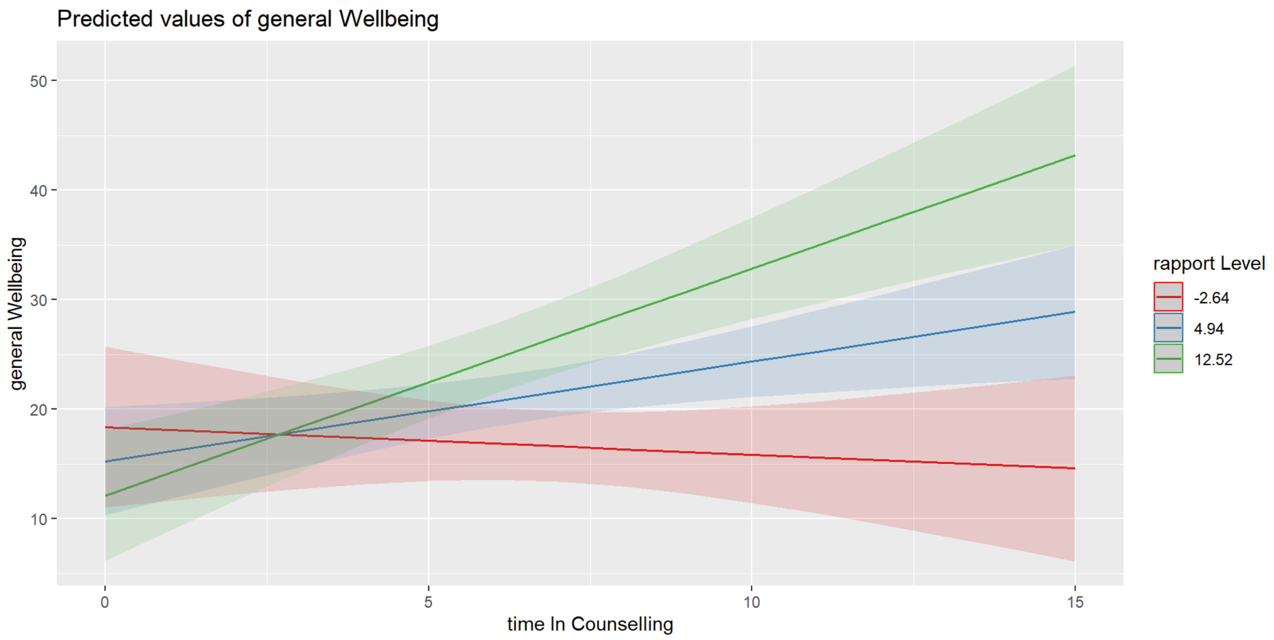
```
Call:
lm(formula = generalWellbeing ~ timeInCounselling * rapportLevel,
    data = modData)

Residuals:
    Min      1Q  Median      3Q     Max
-17.497  -9.119  -0.234   6.125  37.896

Coefficients:
                               Estimate Std. Error t value Pr(>|t|)
(Intercept)                    17.28817    3.14907   5.490 3.28e-07 ***
timeInCounselling               0.15174    0.41507   0.366  0.71548
rapportLevel                   -0.41300    0.30045  -1.375  0.17246
timeInCounselling:rapportLevel  0.15338    0.04031   3.805  0.00025 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 11.36 on 96 degrees of freedom
Multiple R-squared:  0.2763,	Adjusted R-squared:  0.2537
F-statistic: 12.22 on 3 and 96 DF,  p-value: 7.701e-07
```

Interpreting interactions in regression #2

- We can see that the overall model is significant
- We can see that the interaction between timeInCounselling and rapportLevel is significant
- We can see that the main effects of timeInCounselling and rapportLevel are not significant
- In models where the interaction is significant, we should not interpret the main effects of the predictor variables (even when they are significant).

Interpreting interactions in regression #3

- We can look at the **simple slopes** of the interaction.



Interpreting interactions in regression #4

- We can further test this interaction by calculating range of values where the interaction is significant.
- We can do this using the `rockchalk` package. We will do it our moderation example later.

Thinking about interactions

- We can see that the relationship between timeInCounselling and generalWellbeing is different at different levels of rapportLevel.
- This means that the variables are interacting with each other to predict the outcome variable.

⚠ **Warning**

If we plan to test for interactions, we need to make sure that we have enough power to do so. It is more than just adding another predictor, as interaction effects tend to be **much** weaker than main effects.

Moderation designs

What are moderation designs?

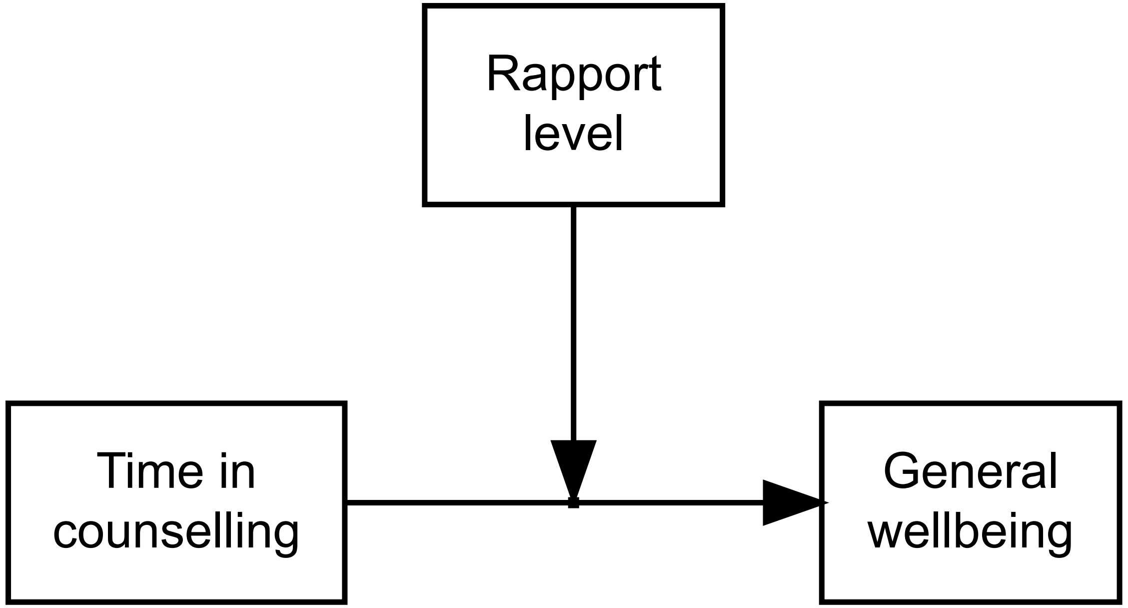
- Moderation designs are when the relationship between two variables is moderated by a third variable.
- This is similar to an interaction, but we are stating our theoretical model about the relationship between the variables in a more specific way.
- For example, we might be interested in whether the relationship between Trait Anxiety and Depression is moderated by Avoidance.
- We are specifically stating that we believe Trait Anxiety predicts Depression, but that their relationship is different at different levels of Avoidance.

So moderation is just an interaction effect?

Statistically, yes. Theoretically, no.

From a theory perspective, we are stating that we believe that the relationship between two variables is moderated by a third variable.

Diagram of moderation design



When should we use moderation designs?

- We should use moderation designs when we have a theoretical reason to believe that the relationship between two variables is moderated by a third variable.
- This should come from a good understanding of the literature and the theory behind the variables.
- We should not use moderation designs “just to see what happens”. The statistical test alone does not **prove** the existence of the theoretical relationship.

How do we check for moderation?

- The first step is to build a regression model that includes the main effects and the interaction between the two predictor variables (this is the same as interaction that we covered earlier).
- If the interaction is significant, we can then visualise the interaction using simple slopes (same as what we did earlier).
- We can then calculate the range of values of the moderator variable where the interaction is significant.

Moderation example

- Let's imagine that we theorise that the relationship between *Time in counselling* and *General Wellbeing* is moderated by *Rapport level*.
- We want to know at which levels of *Rapport level* the relationship between *Time in counselling* and *General Wellbeing* is significant.
- We also want to know the direction of the relationship between *Time in counselling* and *General Wellbeing* at different levels of *Rapport level*.

Moderation example #2

The regression model is the same as the one we used for interactions.

```
# model1 with interactions

model1 <- lm(data = modData, generalWellbeing ~ timeInCounselling * rapportLevel) ①
```

① This model includes an interaction between timeInCounselling and rapportLevel. We know this because we used the * symbol to separate the predictor variables.

Testing the moderation effect

Testing at which levels of *Rapport level* the relationship between *Time in counselling* and *General Wellbeing* is significant.

Step 1: Run the regression model:

```
# model1 with interactions

model1 <- lm(data = modData, generalWellbeing ~ timeInCounselling * rapportLevel)
```

Testing the moderation effect #2

Step 2: Plot the interaction:

```
# model1 with interactions

model1 <- lm(data = modData, generalWellbeing ~ timeInCounselling * rapportLevel)

# using the rockchalk package

library(rockchalk)

# use the plotSlopes() function

ps <- plotSlopes(model1, plotx = "timeInCounselling", modx = "rapportLevel", interval = "co
```

```
ps
```

```
$call
plotSlopes.lm(model = model1, plotx = "timeInCounselling", modx = "rapportLevel",
    modxVals = "std.dev", interval = "confidence")

$newdata
    timeInCounselling rapportLevel      fit       lwr      upr
1           0.0000000        -2.64 18.37848 11.026008 25.73095
2           0.3846154        -2.64 18.28110 11.260845 25.30136
3           0.7692308        -2.64 18.18373 11.491611 24.87585
4           1.1538462        -2.64 18.08636 11.717677 24.45504
5           1.5384615        -2.64 17.98898 11.938290 24.03968
6           1.9230769        -2.64 17.89161 12.152542 23.63068
7           2.3076923        -2.64 17.79424 12.359341 23.22913
8           2.6923077        -2.64 17.69686 12.557361 22.83637
9           3.0769231        -2.64 17.59949 12.745000 22.45398
10          3.4615385        -2.64 17.50212 12.920322 22.08391
11          3.8461538        -2.64 17.40474 13.080993 21.72849
12          4.2307692        -2.64 17.30737 13.224237 21.39050
13          4.6153846        -2.64 17.20999 13.346794 21.07320
14          5.0000000        -2.64 17.11262 13.444943 20.78030
15          5.3846154        -2.64 17.01525 13.514590 20.51591
16          5.7692308        -2.64 16.91787 13.551490 20.28426
17          6.1538462        -2.64 16.82050 13.551607 20.08939
18          6.5384615        -2.64 16.72313 13.511587 19.93467
```

19	6.9230769	-2.64	16.62575	13.429271	19.82224
20	7.3076923	-2.64	16.52838	13.304065	19.75269
21	7.6923077	-2.64	16.43101	13.137056	19.72496
22	8.0769231	-2.64	16.33363	12.930810	19.73645
23	8.4615385	-2.64	16.23626	12.688938	19.78358
24	8.8461538	-2.64	16.13888	12.415585	19.86218
25	9.2307692	-2.64	16.04151	12.114982	19.96804
26	9.6153846	-2.64	15.94414	11.791127	20.09715
27	10.0000000	-2.64	15.84676	11.447610	20.24592
28	10.3846154	-2.64	15.74939	11.087544	20.41124
29	10.7692308	-2.64	15.65202	10.713570	20.59046
30	11.1538462	-2.64	15.55464	10.327895	20.78139
31	11.5384615	-2.64	15.45727	9.932351	20.98219
32	11.9230769	-2.64	15.35990	9.528451	21.19134
33	12.3076923	-2.64	15.26252	9.117446	21.40760
34	12.6923077	-2.64	15.16515	8.700369	21.62993
35	13.0769231	-2.64	15.06778	8.278078	21.85747
36	13.4615385	-2.64	14.97040	7.851288	22.08951
37	13.8461538	-2.64	14.87303	7.420594	22.32546
38	14.2307692	-2.64	14.77565	6.986498	22.56481
39	14.6153846	-2.64	14.67828	6.549423	22.80714
40	15.0000000	-2.64	14.58091	6.109726	23.05209
41	0.0000000	4.94	15.24797	10.313337	20.18259
42	0.3846154	4.94	15.59774	10.890307	20.30518
43	0.7692308	4.94	15.94752	11.463997	20.43104
44	1.1538462	4.94	16.29730	12.033890	20.56070
45	1.5384615	4.94	16.64707	12.599367	20.69478
46	1.9230769	4.94	16.99685	13.159683	20.83402
47	2.3076923	4.94	17.34663	13.713941	20.97931
48	2.6923077	4.94	17.69640	14.261057	21.13175
49	3.0769231	4.94	18.04618	14.799731	21.29263
50	3.4615385	4.94	18.39596	15.328402	21.46351
51	3.8461538	4.94	18.74573	15.845218	21.64625
52	4.2307692	4.94	19.09551	16.348017	21.84300
53	4.6153846	4.94	19.44529	16.834332	22.05624
54	5.0000000	4.94	19.79506	17.301455	22.28867
55	5.3846154	4.94	20.14484	17.746566	22.54311
56	5.7692308	4.94	20.49462	18.166961	22.82227
57	6.1538462	4.94	20.84439	18.560343	23.12844
58	6.5384615	4.94	21.19417	18.925157	23.46318
59	6.9230769	4.94	21.54395	19.260837	23.82706
60	7.3076923	4.94	21.89372	19.567913	24.21953
61	7.6923077	4.94	22.24350	19.847914	24.63909
62	8.0769231	4.94	22.59328	20.103115	25.08344

63	8.4615385	4.94	22.94305	20.336214	25.54989
64	8.8461538	4.94	23.29283	20.550030	26.03563
65	9.2307692	4.94	23.64261	20.747278	26.53794
66	9.6153846	4.94	23.99238	20.930434	27.05433
67	10.0000000	4.94	24.34216	21.101670	27.58265
68	10.3846154	4.94	24.69194	21.262847	28.12103
69	10.7692308	4.94	25.04171	21.415536	28.66789
70	11.1538462	4.94	25.39149	21.561045	29.22194
71	11.5384615	4.94	25.74127	21.700464	29.78207
72	11.9230769	4.94	26.09104	21.834695	30.34739
73	12.3076923	4.94	26.44082	21.964488	30.91715
74	12.6923077	4.94	26.79060	22.090466	31.49073
75	13.0769231	4.94	27.14037	22.213148	32.06760
76	13.4615385	4.94	27.49015	22.332971	32.64733
77	13.8461538	4.94	27.83993	22.450300	33.22956
78	14.2307692	4.94	28.18970	22.565444	33.81397
79	14.6153846	4.94	28.53948	22.678665	34.40030
80	15.0000000	4.94	28.88926	22.790188	34.98833
81	0.0000000	12.52	12.11745	6.158021	18.07688
82	0.3846154	12.52	12.91438	7.224345	18.60441
83	0.7692308	12.52	13.71131	8.284898	19.13772
84	1.1538462	12.52	14.50823	9.338797	19.67767
85	1.5384615	12.52	15.30516	10.385000	20.22532
86	1.9230769	12.52	16.10209	11.422277	20.78190
87	2.3076923	12.52	16.89902	12.449180	21.34885
88	2.6923077	12.52	17.69594	13.464019	21.92787
89	3.0769231	12.52	18.49287	14.464835	22.52090
90	3.4615385	12.52	19.28980	15.449394	23.13020
91	3.8461538	12.52	20.08672	16.415202	23.75824
92	4.2307692	12.52	20.88365	17.359564	24.40774
93	4.6153846	12.52	21.68058	18.279688	25.08147
94	5.0000000	12.52	22.47750	19.172862	25.78215
95	5.3846154	12.52	23.27443	20.036683	26.51218
96	5.7692308	12.52	24.07136	20.869310	27.27341
97	6.1538462	12.52	24.86829	21.669699	28.06687
98	6.5384615	12.52	25.66521	22.437745	28.89268
99	6.9230769	12.52	26.46214	23.174302	29.74998
100	7.3076923	12.52	27.25907	23.881056	30.63708
101	7.6923077	12.52	28.05599	24.560314	31.55168
102	8.0769231	12.52	28.85292	25.214742	32.49110
103	8.4615385	12.52	29.64985	25.847131	33.45257
104	8.8461538	12.52	30.44678	26.460208	34.43334
105	9.2307692	12.52	31.24370	27.056518	35.43089
106	9.6153846	12.52	32.04063	27.638350	36.44291

```
107         10.0000000        12.52 32.83756 28.207724 37.46739
108         10.3846154        12.52 33.63448 28.766385 38.50258
109         10.7692308        12.52 34.43141 29.315830 39.54699
110         11.1538462        12.52 35.22834 29.857333 40.59934
111         11.5384615        12.52 36.02527 30.391975 41.65856
112         11.9230769        12.52 36.82219 30.920669 42.72372
113         12.3076923        12.52 37.61912 31.444191 43.79405
114         12.6923077        12.52 38.41605 31.963199 44.86889
115         13.0769231        12.52 39.21297 32.478251 45.94770
116         13.4615385        12.52 40.00990 32.989824 47.02998
117         13.8461538        12.52 40.80683 33.498325 48.11533
118         14.2307692        12.52 41.60376 34.004104 49.20341
119         14.6153846        12.52 42.40068 34.507462 50.29390
120         15.0000000        12.52 43.19761 35.008660 51.38656

$modxVals
(m-sd)     (m)  (m+sd)
 -2.64    4.94   12.52

$col
     (m-sd)          (m)       (m+sd)
    "black"       "blue" "darkgreen"

$lty
(m-sd)     (m)  (m+sd)
     1       2       3

$fancy
$fancy$col
     (m-sd)          (m)       (m+sd)
    "black"       "blue" "darkgreen"

$fancy$lty
(m-sd)     (m)  (m+sd)
     1       2       3

$fancy$lwd
(m-sd)     (m)  (m+sd)
     2       2       2


attr(,"class")
[1] "plotSlopes" "rockchalk"
```

Testing the moderation effect #3

Step 3: Test the range of values where the interaction is significant:

```
# model1 with interactions

model1 <- lm(data = modData, generalWellbeing ~ timeInCounselling * rapportLevel)

# using the rockchalk package

library(rockchalk)

# use the plotSlopes() function

ps <- plotSlopes(model1, plotx = "timeInCounselling", modx = "rapportLevel", interval = "con
```

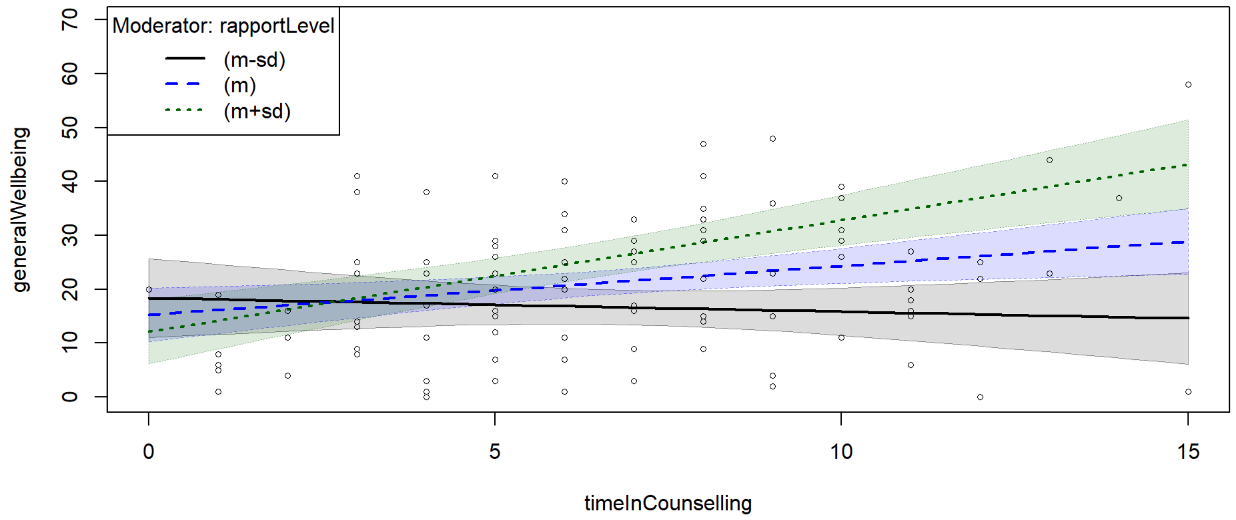
```
# use the testSlopes() function

ts <- testSlopes(ps)
```

```
Values of rapportLevel OUTSIDE this interval:
        lo         hi
-10.828550   3.537184
cause the slope of (b1 + b2*rapportLevel)timeInCounselling to be statistically significant
```

Testing the moderation effect #4

Step 4: Visualise the results:

```
# model1 with interactions

model1 <- lm(data = modData, generalWellbeing ~ timeInCounselling * rapportLevel)

# using the rockchalk package

library(rockchalk)

# use the plotSlopes() function

ps <- plotSlopes(model1, plotx = "timeInCounselling", modx = "rapportLevel", interval = "con
```

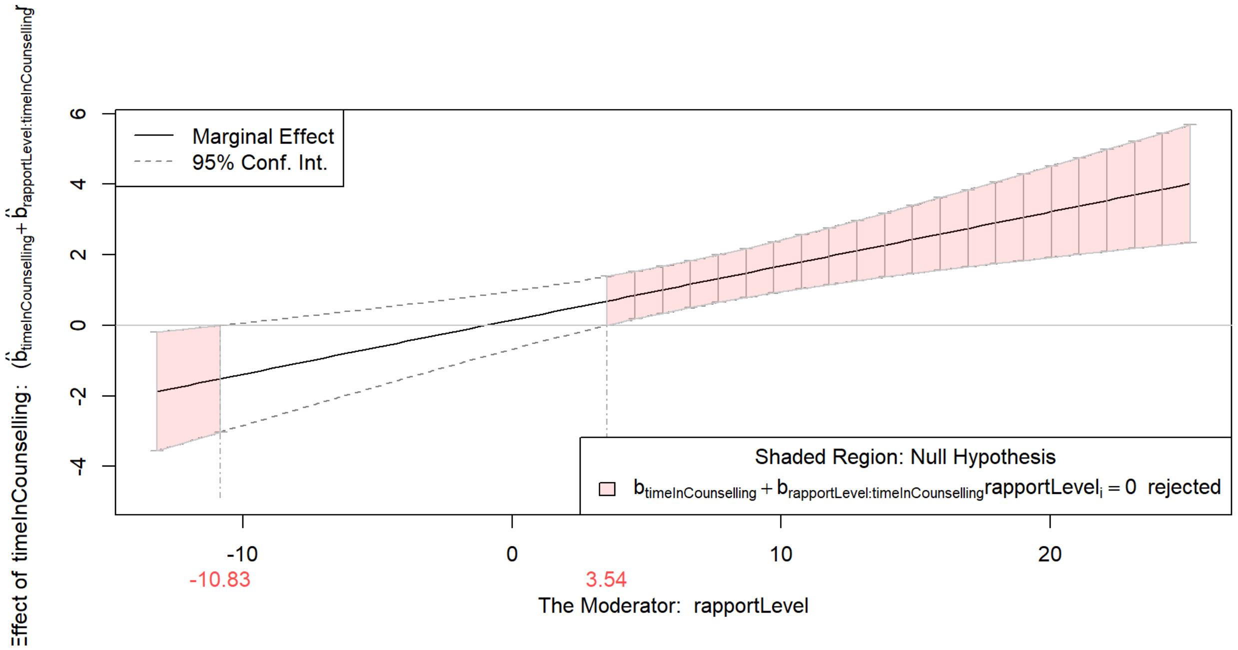



```
# use the testSlopes() function

ts <- testSlopes(ps)
```

```
Values of rapportLevel OUTSIDE this interval:
        lo          hi
```

```
-10.828550   3.537184
cause the slope of (b1 + b2*rapportLevel)timeInCounselling to be statistically significant
```

```r
# plot the range of significant values

plot(ts)
```



How do we interpret the moderation effect?

- We can see that the relationship between *Time in counselling* and *General Wellbeing* is significant levels of *Rapport level* outside of -10.8 and 3.54.
- However, the *Rapport level* scale does not actually go below 0. So we can say that the relationship between *Time in counselling* and *General Wellbeing* is significant when *Rapport level* is above 3.54.
- We can look at the first interaction plot to see the direction of the relationship between *Time in counselling* and *General Wellbeing* at increasing levels of *Rapport level*.

Summary

- We can use regression to model interactions between predictor variables.
- We can also use regression to model moderation of relationships between predictor variables.
- Moderations are just a specific type of interaction. They are based on specific theoretical models about the relationship between variables.
- We can use the `rockchalk` package to test for interactions and moderation and plot them.