Data Analysis for *Not All Risks Are Equal: Female Preferences for Male Risk Taking as a Function of Domain and Social Norms*

2026-03-20

Load packages

```
library("simr")  # for power analysis simulations
library("ggplot2")  # for data visualization
library("lmerTest")  # for data analysis (linear mixed model)
library("ordinal")  # for data analysis (cumulative link mixed model)
library("emmeans")  # for data analysis (pairwise contrasts)
library("DHARMa")  # for assumption checking
library("dplyr")  # for data wrangling
library("tidyr")  # for data wrangling
```

Power analysis

As we do not have detailed predictions for interaction effects or for differences between risk domains, we base the power analysis on detecting the effect of relationship context (short-term vs. long-term) in any individual risk domain (which is of more interest than the overall effect with risk domains combined). Based on Sylwester & Pawłowski (2011), we expect an effect size of *d* ≈ .2 (approximated from *t* value), but this may be smaller in some domains.

```
pID = factor(1:100)  # arbitrary number of participants to initialise model
combinations <- expand.grid(rel_type = c("Short-Term", "Long-Term"),
                            norm_type = c("Conforming", "Violating"), # we do not test for th
is effect here, but including it is an easy way to get the correct number of data points per
participant
                            stringsAsFactors = TRUE)
sim_data = do.call(rbind,
                   lapply(pID, function(id) {
                     df <- combinations
                     df$pID <- id
                     df
                   }))

sim_data <- sim_data[, c("pID", "rel_type", "norm_type")]

# Fixed effects
# 3 for intercept (middle of scale)
# -.2 for LT vs ST slope, based on approx. Cohen's d from Sylwester & Pawłowski (2011)
fixed <- c(3, -.2)

rand <- c(.5)  # variance for random intercept

res <- 1 # residual variance (this should be reasonable, also means slope above = Cohen's d)

model <- makeLmer(y ~ rel_type + (1 | pID), fixef=fixed, VarCorr=rand, sigma=res, data=sim_da
ta)
model
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: y ~ rel_type + (1 | pID)
##    Data: sim_data
## REML criterion at convergence: 1239.13
## Random effects:
##  Groups   Name        Std.Dev.
##  pID      (Intercept) 0.7071
##  Residual             1.0000
## Number of obs: 400, groups:  pID, 100
## Fixed Effects:
##      (Intercept)  rel_typeLong-Term
##              3.0               -0.2
```

For an effect size of *d* = .2, we can estimate the power for various sample sizes:

```
fixef(model)['rel_typeLong-Term'] = -.2

fit_extended_p = extend(model, along = 'pID', n = 1500)

powerCurve(fit_extended_p, fixed('rel_type'),
             along = 'pID', breaks = seq(100,1500,100),
             nsim = 500, seed = 123, progress = FALSE)
```

```
## Power for predictor 'rel_type', (95% confidence interval),
## by number of levels in pID:
##      100: 46.20% (41.76, 50.68) - 400 rows
##      200: 77.80% (73.90, 81.37) - 800 rows
##      300: 92.20% (89.49, 94.39) - 1200 rows
##      400: 97.00% (95.10, 98.31) - 1600 rows
##      500: 98.80% (97.41, 99.56) - 2000 rows
##      600: 99.20% (97.96, 99.78) - 2400 rows
##      700: 99.80% (98.89, 99.99) - 2800 rows
##      800: 99.80% (98.89, 99.99) - 3200 rows
##      900: 100.0% (99.26, 100.0) - 3600 rows
##     1000: 100.0% (99.26, 100.0) - 4000 rows
##     1100: 100.0% (99.26, 100.0) - 4400 rows
##     1200: 100.0% (99.26, 100.0) - 4800 rows
##     1300: 100.0% (99.26, 100.0) - 5200 rows
##     1400: 100.0% (99.26, 100.0) - 5600 rows
##     1500: 100.0% (99.26, 100.0) - 6000 rows
##
## Time elapsed: 0 h 33 m 50 s
```

And for *d* = .1:

```
fixef(model)['rel_typeLong-Term'] = -.1

fit_extended_p = extend(model, along = 'pID', n = 1500)

powerCurve(fit_extended_p, fixed('rel_type'),
             along = 'pID', breaks = seq(100,1500,100),
             nsim = 500, seed = 345, progress = FALSE)
```

```
## Power for predictor 'rel_type', (95% confidence interval),
## by number of levels in pID:
##      100: 16.00% (12.90, 19.51) - 400 rows
##      200: 25.60% (21.83, 29.66) - 800 rows
##      300: 39.80% (35.48, 44.24) - 1200 rows
##      400: 50.40% (45.93, 54.87) - 1600 rows
##      500: 60.00% (55.56, 64.32) - 2000 rows
##      600: 69.00% (64.74, 73.03) - 2400 rows
##      700: 74.80% (70.75, 78.55) - 2800 rows
##      800: 80.60% (76.86, 83.98) - 3200 rows
##      900: 85.00% (81.56, 88.02) - 3600 rows
##     1000: 88.00% (84.82, 90.72) - 4000 rows
##     1100: 91.40% (88.59, 93.71) - 4400 rows
##     1200: 93.20% (90.63, 95.25) - 4800 rows
##     1300: 94.20% (91.78, 96.08) - 5200 rows
##     1400: 96.40% (94.37, 97.85) - 5600 rows
##     1500: 97.00% (95.10, 98.31) - 6000 rows
##
## Time elapsed: 0 h 28 m 29 s
```

A sample size of 1000 is more than adequate for detecting a relationship context effect with *d* = .2 (100% power), while also giving a good opportunity to detect an effect with *d* = .1 (88% power) if the effect is weaker in some risk domains.

Load data

```
data1 = read.csv("data.csv")  # import data

data1$Rel_type = factor(data1$Rel_type, levels=c("ST", "LT"), labels=c("Short-Term", "Long-Te
rm"))
data1$Norm_type = factor(data1$Norm_type, levels=c("NC", "NV"), labels=c("Conforming", "Viola
ting"))
data1$Rt_type = factor(data1$Rt_type, levels=c("Eth", "Fin", "Hth", "Rec", "Soc"), labels=c
("Ethical", "Financial", "Health", "Recreational", "Social"))
```

Linear mixed-effects model

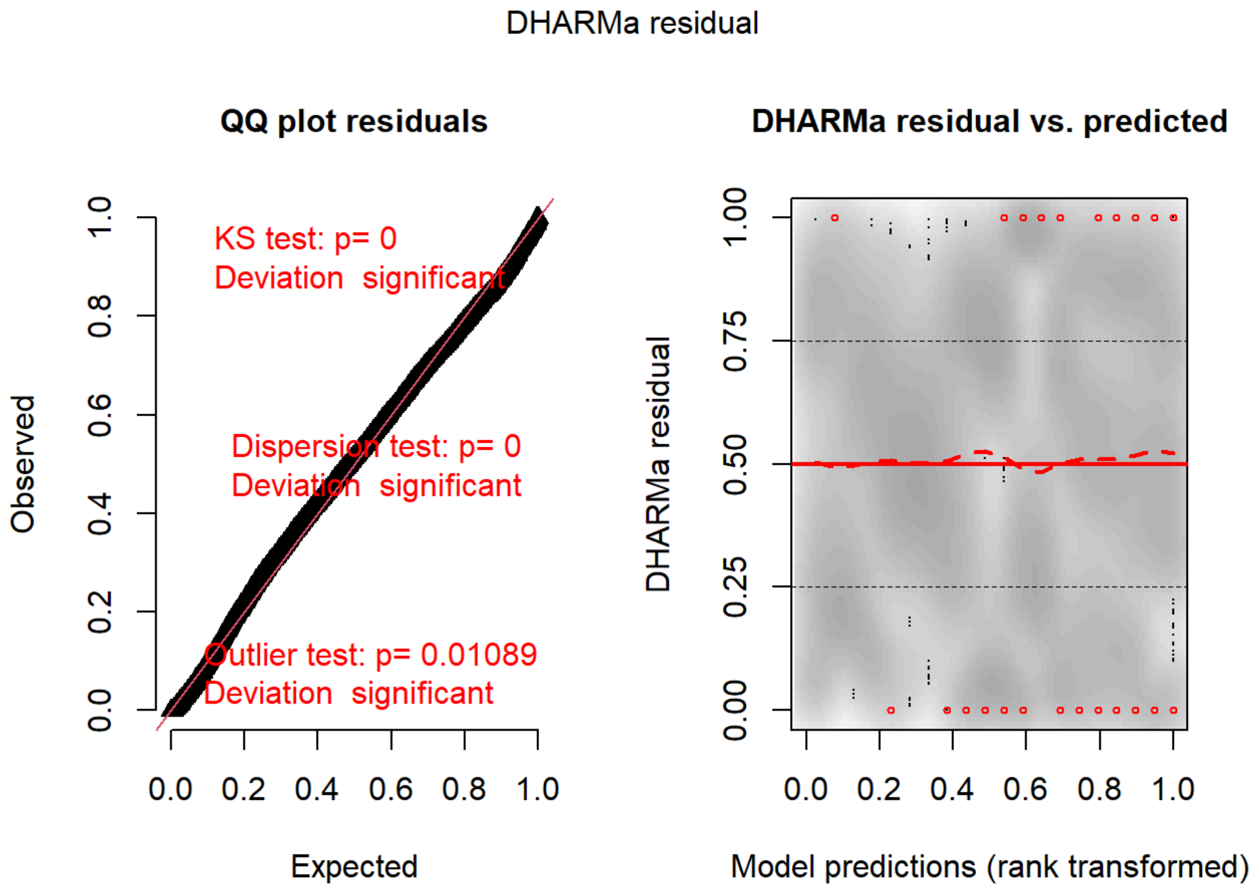
We ran the most maximal model that would converge. This included relationship context, risk domain and norm adherence as interacting fixed effects, a random intercept for participant, and a by-participant random slope for norm adherence.

```
# attempt 1 --> did not converge
# mdl1 = lmer(At_rating ~ Rel_type*Norm_type*Rt_type + (1 + Rel_type + Norm_type + Rt_type |
ID), data=data1, REML=F)

# attempt 2 --> singular fit
#mdl1 = lmer(At_rating ~ Rel_type*Norm_type*Rt_type + (1 + Rel_type + Norm_type | ID), data=d
ata1, REML=F)

# attempt 3 --> did not converge
#mdl1 = lmer(At_rating ~ Rel_type*Norm_type*Rt_type + (1 + Rel_type + Rt_type | ID), data=dat
a1, REML=F)

# attempt 4 --> did not converge
#mdl1 = lmer(At_rating ~ Rel_type*Norm_type*Rt_type + (1 + Norm_type + Rt_type | ID), data=da
ta1, REML=F)

# attempt 5 --> singular fit
#mdl1 = lmer(At_rating ~ Rel_type*Norm_type*Rt_type + (1 + Rel_type | ID), data=data1, REML=
F)

# attempt 6 --> did not converge
#mdl1 = lmer(At_rating ~ Rel_type*Norm_type*Rt_type + (1 + Rt_type | ID), data=data1, REML=F)

# attempt 7 --> converged
mdl1 = lmer(At_rating ~ Rel_type*Norm_type*Rt_type + (1 + Norm_type | ID), data=data1, REML=
F)
```

Assumption tests

Residuals look okay in terms of normality and homoscedasticity (DHARMa’s various tests are significant, but this is likely due to the large sample size – visually this looks fine).

```
plot(simulateResiduals(fittedModel = mdl1, use.u = T))
```



Convergence diagnostics

The model converged successfully (maximum gradient < 0.001; Hessian positive definite).

```
# scaled max gradient (should be very low)
max(abs(with(mdl1@optinfo$derivs, solve(Hessian, gradient))))
```

```
## [1] 1.071449e-05
```

```
# check Hessian is positive definite (should be true)
all(eigen(vcov(mdl1))$values > 0)
```

```
## [1] TRUE
```

Model output

```
summary(mdl1)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: At_rating ~ Rel_type * Norm_type * Rt_type + (1 + Norm_type |      ID)
##    Data: data1
##
##      AIC      BIC   logLik deviance df.resid
##  46738.9  46928.5 -23345.4  46690.9    19976
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.9727 -0.5795  0.0412  0.6697  3.7118
##
## Random effects:
##  Groups   Name              Variance Std.Dev. Corr
##  ID       (Intercept)       0.21968  0.4687
##           Norm_typeViolating 0.01473  0.1214   -0.49
##  Residual                   0.54103  0.7355
## Number of obs: 20000, groups:  ID, 1000
##
## Fixed effects:
##                                                          Estimate Std. Error
## (Intercept)                                             3.857e+00  2.758e-02
## Rel_typeLong-Term                                      -6.140e-01  3.289e-02
## Norm_typeViolating                                     -5.870e-01  3.312e-02
## Rt_typeFinancial                                       -1.077e+00  3.289e-02
## Rt_typeHealth                                           1.620e-01  3.289e-02
## Rt_typeRecreational                                     4.100e-02  3.289e-02
## Rt_typeSocial                                          -7.300e-02  3.289e-02
## Rel_typeLong-Term:Norm_typeViolating                    1.430e-01  4.652e-02
## Rel_typeLong-Term:Rt_typeFinancial                      7.900e-02  4.652e-02
## Rel_typeLong-Term:Rt_typeHealth                         2.970e-01  4.652e-02
## Rel_typeLong-Term:Rt_typeRecreational                  -1.670e-01  4.652e-02
## Rel_typeLong-Term:Rt_typeSocial                         1.360e-01  4.652e-02
## Norm_typeViolating:Rt_typeFinancial                     1.970e-01  4.652e-02
## Norm_typeViolating:Rt_typeHealth                        2.680e-01  4.652e-02
## Norm_typeViolating:Rt_typeRecreational                 -4.440e-01  4.652e-02
## Norm_typeViolating:Rt_typeSocial                        9.900e-02  4.652e-02
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeFinancial     1.430e-01  6.579e-02
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeHealth       -2.910e-01  6.579e-02
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeRecreational  3.670e-01  6.579e-02
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeSocial        1.860e-01  6.579e-02
##                                                                df t value
## (Intercept)                                             6.566e+03 139.842
## Rel_typeLong-Term                                       1.800e+04 -18.666
## Norm_typeViolating                                      1.774e+04 -17.725
## Rt_typeFinancial                                        1.800e+04 -32.741
## Rt_typeHealth                                           1.800e+04   4.925
## Rt_typeRecreational                                     1.800e+04   1.246
## Rt_typeSocial                                           1.800e+04  -2.219
## Rel_typeLong-Term:Norm_typeViolating                    1.800e+04   3.074
## Rel_typeLong-Term:Rt_typeFinancial                      1.800e+04   1.698
## Rel_typeLong-Term:Rt_typeHealth                         1.800e+04   6.384
## Rel_typeLong-Term:Rt_typeRecreational                   1.800e+04  -3.590
## Rel_typeLong-Term:Rt_typeSocial                         1.800e+04   2.923
## Norm_typeViolating:Rt_typeFinancial                     1.800e+04   4.235
```

```
## Norm_typeViolating:Rt_typeHealth                          1.800e+04   5.761
## Norm_typeViolating:Rt_typeRecreational                    1.800e+04  -9.544
## Norm_typeViolating:Rt_typeSocial                          1.800e+04   2.128
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeFinancial     1.800e+04   2.174
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeHealth        1.800e+04  -4.423
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeRecreational  1.800e+04   5.578
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeSocial        1.800e+04   2.827
##                                                          Pr(>|t|)
## (Intercept)                                               < 2e-16 ***
## Rel_typeLong-Term                                         < 2e-16 ***
## Norm_typeViolating                                        < 2e-16 ***
## Rt_typeFinancial                                          < 2e-16 ***
## Rt_typeHealth                                            8.52e-07 ***
## Rt_typeRecreational                                      0.212634
## Rt_typeSocial                                            0.026486 *
## Rel_typeLong-Term:Norm_typeViolating                     0.002116 **
## Rel_typeLong-Term:Rt_typeFinancial                       0.089490 .
## Rel_typeLong-Term:Rt_typeHealth                          1.76e-10 ***
## Rel_typeLong-Term:Rt_typeRecreational                    0.000332 ***
## Rel_typeLong-Term:Rt_typeSocial                          0.003466 **
## Norm_typeViolating:Rt_typeFinancial                      2.30e-05 ***
## Norm_typeViolating:Rt_typeHealth                         8.50e-09 ***
## Norm_typeViolating:Rt_typeRecreational                    < 2e-16 ***
## Norm_typeViolating:Rt_typeSocial                         0.033342 *
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeFinancial    0.029748 *
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeHealth       9.78e-06 ***
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeRecreational 2.46e-08 ***
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeSocial       0.004701 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Correlation matrix not shown by default, as p = 20 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

95% confidence intervals for effects

```
# get 95% CIs on effects
confint(mdl1, method = "boot", nsim = 1000)
```

```
## Computing bootstrap confidence intervals ...
```

```
##
## 10 message(s): boundary (singular) fit: see help('isSingular')
## 56 warning(s): Model failed to converge with max|grad| = 0.00206263 (tol = 0.002, componen
t 1) (and others)
```

```
##                                                                 2.5 %
## .sig01                                                    0.440338143
## .sig02                                                   -0.815030823
## .sig03                                                    0.063487944
## .sigma                                                    0.727404161
## (Intercept)                                               3.803841012
## Rel_typeLong-Term                                        -0.682146156
## Norm_typeViolating                                       -0.654573588
## Rt_typeFinancial                                         -1.139088642
## Rt_typeHealth                                             0.097353879
## Rt_typeRecreational                                      -0.026784064
## Rt_typeSocial                                            -0.140723566
## Rel_typeLong-Term:Norm_typeViolating                      0.055563004
## Rel_typeLong-Term:Rt_typeFinancial                       -0.013863984
## Rel_typeLong-Term:Rt_typeHealth                           0.209110842
## Rel_typeLong-Term:Rt_typeRecreational                    -0.263061336
## Rel_typeLong-Term:Rt_typeSocial                           0.043767739
## Norm_typeViolating:Rt_typeFinancial                       0.105175186
## Norm_typeViolating:Rt_typeHealth                          0.176136039
## Norm_typeViolating:Rt_typeRecreational                   -0.541179205
## Norm_typeViolating:Rt_typeSocial                          0.008060796
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeFinancial     0.013496003
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeHealth       -0.424660029
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeRecreational  0.243394194
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeSocial        0.056490282
##                                                                97.5 %
## .sig01                                                    0.494261368
## .sig02                                                   -0.334671555
## .sig03                                                    0.160904156
## .sigma                                                    0.742635241
## (Intercept)                                               3.912628292
## Rel_typeLong-Term                                        -0.551982724
## Norm_typeViolating                                       -0.524238396
## Rt_typeFinancial                                         -1.015233089
## Rt_typeHealth                                             0.228293816
## Rt_typeRecreational                                       0.109663887
## Rt_typeSocial                                            -0.009494808
## Rel_typeLong-Term:Norm_typeViolating                      0.236781540
## Rel_typeLong-Term:Rt_typeFinancial                        0.161190394
## Rel_typeLong-Term:Rt_typeHealth                           0.389616141
## Rel_typeLong-Term:Rt_typeRecreational                    -0.079165479
## Rel_typeLong-Term:Rt_typeSocial                           0.226848739
## Norm_typeViolating:Rt_typeFinancial                       0.287726190
## Norm_typeViolating:Rt_typeHealth                          0.358209375
## Norm_typeViolating:Rt_typeRecreational                   -0.346948195
## Norm_typeViolating:Rt_typeSocial                          0.188913860
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeFinancial     0.264470027
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeHealth       -0.167888647
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeRecreational  0.489423278
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeSocial        0.317898551
```

Intraclass correlations (ICCs)

```
icc = function(slope_level, intercept_var, slope_var, correl, resid_var){
    covar = correl * sqrt(intercept_var) * sqrt(slope_var)
    return ((intercept_var + (2*slope_level*covar) + ((slope_level^2)*slope_var))/(intercept_
var + (2*slope_level*covar) + ((slope_level^2)*slope_var) + resid_var))
}

mdl1_raneff = as.data.frame(lme4::VarCorr(mdl1))

icc(0, mdl1_raneff$vcov[1], mdl1_raneff$vcov[2], mdl1_raneff$sdcor[3], mdl1_raneff$vcov[4])
# for norm-conforming
```

```
## [1] 0.2887867
```

```
icc(1, mdl1_raneff$vcov[1], mdl1_raneff$vcov[2], mdl1_raneff$sdcor[3], mdl1_raneff$vcov[4])
# for norm-violating
```

```
## [1] 0.248018
```

Pairwise contrasts

```
emmeans(mdl1, pairwise~Rel_type | Rt_type)
```

```
## $emmeans
## Rt_type = Ethical:
##  Rel_type   emmean     SE  df asymp.LCL asymp.UCL
##  Short-Term   3.56 0.0216 Inf      3.52      3.61
##  Long-Term    3.02 0.0216 Inf      2.98      3.06
##
## Rt_type = Financial:
##  Rel_type   emmean     SE  df asymp.LCL asymp.UCL
##  Short-Term   2.58 0.0216 Inf      2.54      2.63
##  Long-Term    2.19 0.0216 Inf      2.15      2.24
##
## Rt_type = Health:
##  Rel_type   emmean     SE  df asymp.LCL asymp.UCL
##  Short-Term   3.86 0.0216 Inf      3.82      3.90
##  Long-Term    3.47 0.0216 Inf      3.43      3.51
##
## Rt_type = Recreational:
##  Rel_type   emmean     SE  df asymp.LCL asymp.UCL
##  Short-Term   3.38 0.0216 Inf      3.34      3.42
##  Long-Term    2.86 0.0216 Inf      2.81      2.90
##
## Rt_type = Social:
##  Rel_type   emmean     SE  df asymp.LCL asymp.UCL
##  Short-Term   3.54 0.0216 Inf      3.50      3.58
##  Long-Term    3.23 0.0216 Inf      3.18      3.27
##
## Results are averaged over the levels of: Norm_type
## Degrees-of-freedom method: asymptotic
## Confidence level used: 0.95
##
## $contrasts
## Rt_type = Ethical:
##  contrast                  estimate     SE  df z.ratio p.value
##  (Short-Term) - (Long-Term)    0.542 0.0233 Inf  23.323  <.0001
##
## Rt_type = Financial:
##  contrast                  estimate     SE  df z.ratio p.value
##  (Short-Term) - (Long-Term)    0.392 0.0233 Inf  16.853  <.0001
##
## Rt_type = Health:
##  contrast                  estimate     SE  df z.ratio p.value
##  (Short-Term) - (Long-Term)    0.391 0.0233 Inf  16.810  <.0001
##
## Rt_type = Recreational:
##  contrast                  estimate     SE  df z.ratio p.value
##  (Short-Term) - (Long-Term)    0.526 0.0233 Inf  22.614  <.0001
##
## Rt_type = Social:
##  contrast                  estimate     SE  df z.ratio p.value
##  (Short-Term) - (Long-Term)    0.314 0.0233 Inf  13.478  <.0001
##
## Results are averaged over the levels of: Norm_type
## Degrees-of-freedom method: asymptotic
```

```
# correct p values for multiple comparisons
p_list = summary(emmeans(mdl1, pairwise~Rel_type | Rt_type)$contrasts)$p.value
round(p.adjust(p_list, method = "holm", n = length(p_list)), digits=3)
```

```
## [1] 0 0 0 0 0
```

```
# get 95% CIs
confint(emmeans(mdl1, pairwise~Rel_type | Rt_type), adjust = "holm", level = 0.95)
```

```
## $emmeans
## Rt_type = Ethical:
##  Rel_type   emmean     SE  df asymp.LCL asymp.UCL
##  Short-Term   3.56 0.0216 Inf      3.52      3.61
##  Long-Term    3.02 0.0216 Inf      2.97      3.07
##
## Rt_type = Financial:
##  Rel_type   emmean     SE  df asymp.LCL asymp.UCL
##  Short-Term   2.58 0.0216 Inf      2.54      2.63
##  Long-Term    2.19 0.0216 Inf      2.14      2.24
##
## Rt_type = Health:
##  Rel_type   emmean     SE  df asymp.LCL asymp.UCL
##  Short-Term   3.86 0.0216 Inf      3.81      3.91
##  Long-Term    3.47 0.0216 Inf      3.42      3.52
##
## Rt_type = Recreational:
##  Rel_type   emmean     SE  df asymp.LCL asymp.UCL
##  Short-Term   3.38 0.0216 Inf      3.33      3.43
##  Long-Term    2.86 0.0216 Inf      2.81      2.90
##
## Rt_type = Social:
##  Rel_type   emmean     SE  df asymp.LCL asymp.UCL
##  Short-Term   3.54 0.0216 Inf      3.49      3.59
##  Long-Term    3.23 0.0216 Inf      3.18      3.27
##
## Results are averaged over the levels of: Norm_type
## Degrees-of-freedom method: asymptotic
## Confidence level used: 0.95
## Conf-level adjustment: bonferroni method for 2 estimates
##
## $contrasts
## Rt_type = Ethical:
##  contrast                   estimate     SE  df asymp.LCL asymp.UCL
##  (Short-Term) - (Long-Term)    0.542 0.0233 Inf     0.497     0.588
##
## Rt_type = Financial:
##  contrast                   estimate     SE  df asymp.LCL asymp.UCL
##  (Short-Term) - (Long-Term)    0.392 0.0233 Inf     0.346     0.438
##
## Rt_type = Health:
##  contrast                   estimate     SE  df asymp.LCL asymp.UCL
##  (Short-Term) - (Long-Term)    0.391 0.0233 Inf     0.345     0.437
##
## Rt_type = Recreational:
##  contrast                   estimate     SE  df asymp.LCL asymp.UCL
##  (Short-Term) - (Long-Term)    0.526 0.0233 Inf     0.480     0.572
##
## Rt_type = Social:
##  contrast                   estimate     SE  df asymp.LCL asymp.UCL
##  (Short-Term) - (Long-Term)    0.314 0.0233 Inf     0.268     0.359
##
## Results are averaged over the levels of: Norm_type
## Degrees-of-freedom method: asymptotic
## Confidence level used: 0.95
```

```
# Cohen's d
eff_size(emmeans(mdl1, pairwise~Rel_type | Rt_type), sigma = sigma(mdl1), edf = Inf)
```

```
## Rt_type = Ethical:
##  contrast                     effect.size     SE  df asymp.LCL asymp.UCL
##  ((Short-Term) - (Long-Term))       0.738 0.0316 Inf     0.676     0.800
##
## Rt_type = Financial:
##  contrast                     effect.size     SE  df asymp.LCL asymp.UCL
##  ((Short-Term) - (Long-Term))       0.533 0.0316 Inf     0.471     0.595
##
## Rt_type = Health:
##  contrast                     effect.size     SE  df asymp.LCL asymp.UCL
##  ((Short-Term) - (Long-Term))       0.532 0.0316 Inf     0.470     0.594
##
## Rt_type = Recreational:
##  contrast                     effect.size     SE  df asymp.LCL asymp.UCL
##  ((Short-Term) - (Long-Term))       0.715 0.0316 Inf     0.653     0.777
##
## Rt_type = Social:
##  contrast                     effect.size     SE  df asymp.LCL asymp.UCL
##  ((Short-Term) - (Long-Term))       0.426 0.0316 Inf     0.364     0.488
##
## Results are averaged over the levels of: Norm_type
## sigma used for effect sizes: 0.7355
## Degrees-of-freedom method: inherited from asymptotic when re-gridding
## Confidence level used: 0.95
```

```
emmeans(mdl1, pairwise~Norm_type | Rel_type*Rt_type)
```

```
## $emmeans
## Rel_type = Short-Term, Rt_type = Ethical:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   3.86 0.0276 Inf      3.80      3.91
##  Violating    3.27 0.0268 Inf      3.22      3.32
##
## Rel_type = Long-Term, Rt_type = Ethical:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   3.24 0.0276 Inf      3.19      3.30
##  Violating    2.80 0.0268 Inf      2.75      2.85
##
## Rel_type = Short-Term, Rt_type = Financial:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   2.78 0.0276 Inf      2.73      2.83
##  Violating    2.39 0.0268 Inf      2.34      2.44
##
## Rel_type = Long-Term, Rt_type = Financial:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   2.25 0.0276 Inf      2.19      2.30
##  Violating    2.14 0.0268 Inf      2.09      2.19
##
## Rel_type = Short-Term, Rt_type = Health:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   4.02 0.0276 Inf      3.96      4.07
##  Violating    3.70 0.0268 Inf      3.65      3.75
##
## Rel_type = Long-Term, Rt_type = Health:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   3.70 0.0276 Inf      3.65      3.76
##  Violating    3.23 0.0268 Inf      3.18      3.29
##
## Rel_type = Short-Term, Rt_type = Recreational:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   3.90 0.0276 Inf      3.84      3.95
##  Violating    2.87 0.0268 Inf      2.81      2.92
##
## Rel_type = Long-Term, Rt_type = Recreational:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   3.12 0.0276 Inf      3.06      3.17
##  Violating    2.60 0.0268 Inf      2.54      2.65
##
## Rel_type = Short-Term, Rt_type = Social:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   3.78 0.0276 Inf      3.73      3.84
##  Violating    3.30 0.0268 Inf      3.24      3.35
##
## Rel_type = Long-Term, Rt_type = Social:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   3.31 0.0276 Inf      3.25      3.36
##  Violating    3.15 0.0268 Inf      3.09      3.20
##
## Degrees-of-freedom method: asymptotic
## Confidence level used: 0.95
##
## $contrasts
```

```
## Rel_type = Short-Term, Rt_type = Ethical:
##  contrast               estimate     SE  df z.ratio p.value
##  Conforming - Violating    0.587 0.0331 Inf  17.725  <.0001
##
## Rel_type = Long-Term, Rt_type = Ethical:
##  contrast               estimate     SE  df z.ratio p.value
##  Conforming - Violating    0.444 0.0331 Inf  13.407  <.0001
##
## Rel_type = Short-Term, Rt_type = Financial:
##  contrast               estimate     SE  df z.ratio p.value
##  Conforming - Violating    0.390 0.0331 Inf  11.776  <.0001
##
## Rel_type = Long-Term, Rt_type = Financial:
##  contrast               estimate     SE  df z.ratio p.value
##  Conforming - Violating    0.104 0.0331 Inf   3.140  0.0017
##
## Rel_type = Short-Term, Rt_type = Health:
##  contrast               estimate     SE  df z.ratio p.value
##  Conforming - Violating    0.319 0.0331 Inf   9.632  <.0001
##
## Rel_type = Long-Term, Rt_type = Health:
##  contrast               estimate     SE  df z.ratio p.value
##  Conforming - Violating    0.467 0.0331 Inf  14.101  <.0001
##
## Rel_type = Short-Term, Rt_type = Recreational:
##  contrast               estimate     SE  df z.ratio p.value
##  Conforming - Violating    1.031 0.0331 Inf  31.131  <.0001
##
## Rel_type = Long-Term, Rt_type = Recreational:
##  contrast               estimate     SE  df z.ratio p.value
##  Conforming - Violating    0.521 0.0331 Inf  15.732  <.0001
##
## Rel_type = Short-Term, Rt_type = Social:
##  contrast               estimate     SE  df z.ratio p.value
##  Conforming - Violating    0.488 0.0331 Inf  14.735  <.0001
##
## Rel_type = Long-Term, Rt_type = Social:
##  contrast               estimate     SE  df z.ratio p.value
##  Conforming - Violating    0.159 0.0331 Inf   4.801  <.0001
##
## Degrees-of-freedom method: asymptotic
```

```
# correct p values for multiple comparisons
p_list = summary(emmeans(mdl1, pairwise~Norm_type | Rel_type*Rt_type)$contrasts)$p.value
round(p.adjust(p_list, method = "holm", n = length(p_list)), digits=3)
```

```
##  [1] 0.000 0.000 0.000 0.002 0.000 0.000 0.000 0.000 0.000 0.000
```

```
# get 95% CIs
confint(emmeans(mdl1, pairwise~Norm_type | Rel_type*Rt_type), adjust = "holm", level = 0.95)
```

```
## $emmeans
## Rel_type = Short-Term, Rt_type = Ethical:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   3.86 0.0276 Inf      3.80      3.92
##  Violating    3.27 0.0268 Inf      3.21      3.33
##
## Rel_type = Long-Term, Rt_type = Ethical:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   3.24 0.0276 Inf      3.18      3.30
##  Violating    2.80 0.0268 Inf      2.74      2.86
##
## Rel_type = Short-Term, Rt_type = Financial:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   2.78 0.0276 Inf      2.72      2.84
##  Violating    2.39 0.0268 Inf      2.33      2.45
##
## Rel_type = Long-Term, Rt_type = Financial:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   2.25 0.0276 Inf      2.18      2.31
##  Violating    2.14 0.0268 Inf      2.08      2.20
##
## Rel_type = Short-Term, Rt_type = Health:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   4.02 0.0276 Inf      3.96      4.08
##  Violating    3.70 0.0268 Inf      3.64      3.76
##
## Rel_type = Long-Term, Rt_type = Health:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   3.70 0.0276 Inf      3.64      3.76
##  Violating    3.23 0.0268 Inf      3.17      3.30
##
## Rel_type = Short-Term, Rt_type = Recreational:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   3.90 0.0276 Inf      3.84      3.96
##  Violating    2.87 0.0268 Inf      2.81      2.93
##
## Rel_type = Long-Term, Rt_type = Recreational:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   3.12 0.0276 Inf      3.06      3.18
##  Violating    2.60 0.0268 Inf      2.54      2.66
##
## Rel_type = Short-Term, Rt_type = Social:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   3.78 0.0276 Inf      3.72      3.85
##  Violating    3.30 0.0268 Inf      3.24      3.36
##
## Rel_type = Long-Term, Rt_type = Social:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming   3.31 0.0276 Inf      3.24      3.37
##  Violating    3.15 0.0268 Inf      3.09      3.21
##
## Degrees-of-freedom method: asymptotic
## Confidence level used: 0.95
## Conf-level adjustment: bonferroni method for 2 estimates
##
```

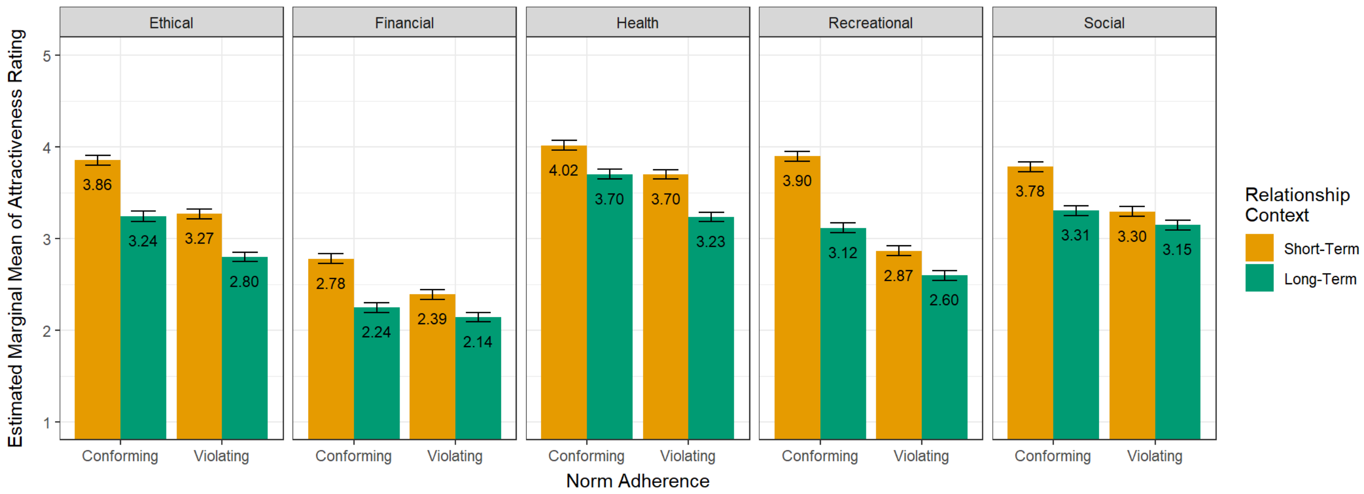
```
## $contrasts
## Rel_type = Short-Term, Rt_type = Ethical:
##  contrast               estimate     SE  df asymp.LCL asymp.UCL
##  Conforming - Violating    0.587 0.0331 Inf    0.5221     0.652
##
## Rel_type = Long-Term, Rt_type = Ethical:
##  contrast               estimate     SE  df asymp.LCL asymp.UCL
##  Conforming - Violating    0.444 0.0331 Inf    0.3791     0.509
##
## Rel_type = Short-Term, Rt_type = Financial:
##  contrast               estimate     SE  df asymp.LCL asymp.UCL
##  Conforming - Violating    0.390 0.0331 Inf    0.3251     0.455
##
## Rel_type = Long-Term, Rt_type = Financial:
##  contrast               estimate     SE  df asymp.LCL asymp.UCL
##  Conforming - Violating    0.104 0.0331 Inf    0.0391     0.169
##
## Rel_type = Short-Term, Rt_type = Health:
##  contrast               estimate     SE  df asymp.LCL asymp.UCL
##  Conforming - Violating    0.319 0.0331 Inf    0.2541     0.384
##
## Rel_type = Long-Term, Rt_type = Health:
##  contrast               estimate     SE  df asymp.LCL asymp.UCL
##  Conforming - Violating    0.467 0.0331 Inf    0.4021     0.532
##
## Rel_type = Short-Term, Rt_type = Recreational:
##  contrast               estimate     SE  df asymp.LCL asymp.UCL
##  Conforming - Violating    1.031 0.0331 Inf    0.9661     1.096
##
## Rel_type = Long-Term, Rt_type = Recreational:
##  contrast               estimate     SE  df asymp.LCL asymp.UCL
##  Conforming - Violating    0.521 0.0331 Inf    0.4561     0.586
##
## Rel_type = Short-Term, Rt_type = Social:
##  contrast               estimate     SE  df asymp.LCL asymp.UCL
##  Conforming - Violating    0.488 0.0331 Inf    0.4231     0.553
##
## Rel_type = Long-Term, Rt_type = Social:
##  contrast               estimate     SE  df asymp.LCL asymp.UCL
##  Conforming - Violating    0.159 0.0331 Inf    0.0941     0.224
##
## Degrees-of-freedom method: asymptotic
## Confidence level used: 0.95
```

```
# Cohen's d
eff_size(emmeans(mdl1, pairwise~Norm_type | Rel_type*Rt_type), sigma = sigma(mdl1), edf = In
f)
```

```
## Rel_type = Short-Term, Rt_type = Ethical:
##  contrast                 effect.size    SE  df asymp.LCL asymp.UCL
##  (Conforming - Violating)       0.798 0.045 Inf    0.7098     0.886
##
## Rel_type = Long-Term, Rt_type = Ethical:
##  contrast                 effect.size    SE  df asymp.LCL asymp.UCL
##  (Conforming - Violating)       0.604 0.045 Inf    0.5154     0.692
##
## Rel_type = Short-Term, Rt_type = Financial:
##  contrast                 effect.size    SE  df asymp.LCL asymp.UCL
##  (Conforming - Violating)       0.530 0.045 Inf    0.4420     0.618
##
## Rel_type = Long-Term, Rt_type = Financial:
##  contrast                 effect.size    SE  df asymp.LCL asymp.UCL
##  (Conforming - Violating)       0.141 0.045 Inf    0.0531     0.230
##
## Rel_type = Short-Term, Rt_type = Health:
##  contrast                 effect.size    SE  df asymp.LCL asymp.UCL
##  (Conforming - Violating)       0.434 0.045 Inf    0.3454     0.522
##
## Rel_type = Long-Term, Rt_type = Health:
##  contrast                 effect.size    SE  df asymp.LCL asymp.UCL
##  (Conforming - Violating)       0.635 0.045 Inf    0.5467     0.723
##
## Rel_type = Short-Term, Rt_type = Recreational:
##  contrast                 effect.size    SE  df asymp.LCL asymp.UCL
##  (Conforming - Violating)       1.402 0.045 Inf    1.3134     1.490
##
## Rel_type = Long-Term, Rt_type = Recreational:
##  contrast                 effect.size    SE  df asymp.LCL asymp.UCL
##  (Conforming - Violating)       0.708 0.045 Inf    0.6201     0.797
##
## Rel_type = Short-Term, Rt_type = Social:
##  contrast                 effect.size    SE  df asymp.LCL asymp.UCL
##  (Conforming - Violating)       0.663 0.045 Inf    0.5752     0.752
##
## Rel_type = Long-Term, Rt_type = Social:
##  contrast                 effect.size    SE  df asymp.LCL asymp.UCL
##  (Conforming - Violating)       0.216 0.045 Inf    0.1279     0.304
##
## sigma used for effect sizes: 0.7355
## Degrees-of-freedom method: inherited from asymptotic when re-gridding
## Confidence level used: 0.95
```

Figure

```
fig1 = ggplot(as.data.frame(emmeans(mdl1, ~ Rel_type*Rt_type*Norm_type)), aes(x=Norm_type, y=
emmean, fill=Rel_type)) +
  facet_grid(.~Rt_type) +
  geom_col(position="dodge") +
  geom_errorbar(aes(ymin=asymp.LCL, ymax=asymp.UCL), colour="black", position=position_dodge
(width=0.9), width=.5) +
  geom_text(aes(label=format(round(emmean, 2), nsmall = 2)), position=position_dodge(width=.
9), vjust=2.5, size=3) +
  theme_bw() +
  scale_fill_manual(values=c("#e69f00", "#009e73")) +
  labs(x="Norm Adherence", y="Estimated Marginal Mean of Attractiveness Rating", fill="Relati
onship\nContext") +
  coord_cartesian(ylim=c(1,5)) +
  theme(axis.title.y = element_text(margin = margin(r = 10)), axis.title.x = element_text(mar
gin = margin(t = 5)))
fig1
```



Cumulative link mixed-effects model

Although the linear model is more interpretable, for ordinal data (from a Likert scale) a cumulative link model is more appropriate. Here we re-run the analysis using a cumulative link model to check that the results are comparable.

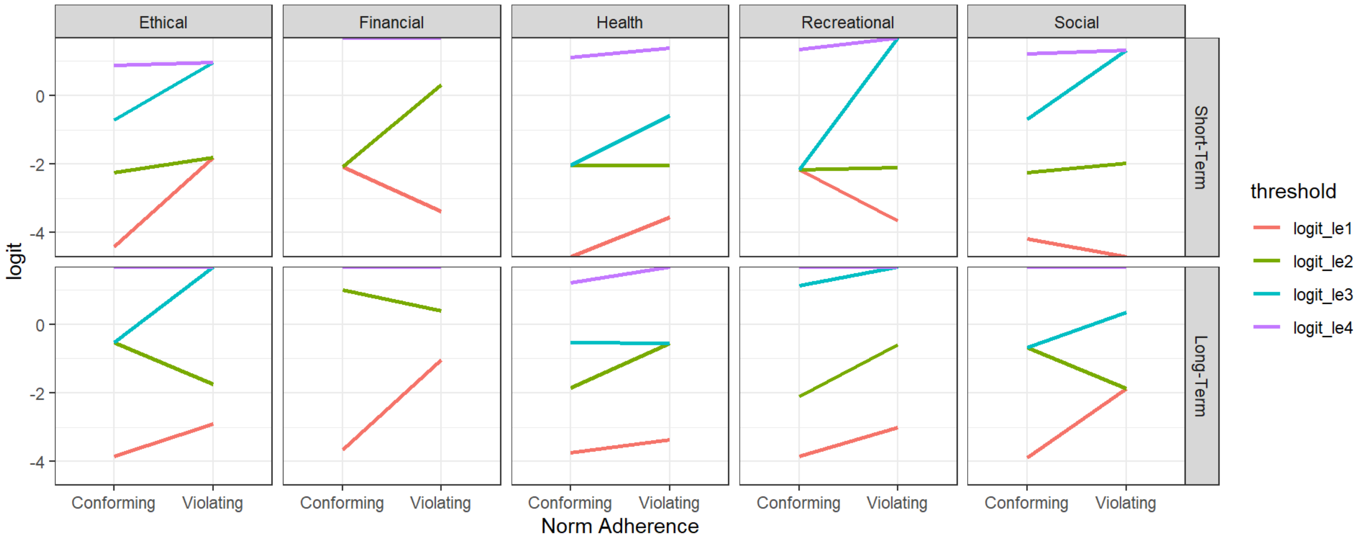
```
mdl2 = clmm(factor(At_rating) ~ Rel_type*Norm_type*Rt_type + (Norm_type | ID), data=data1)
```

Assumption tests

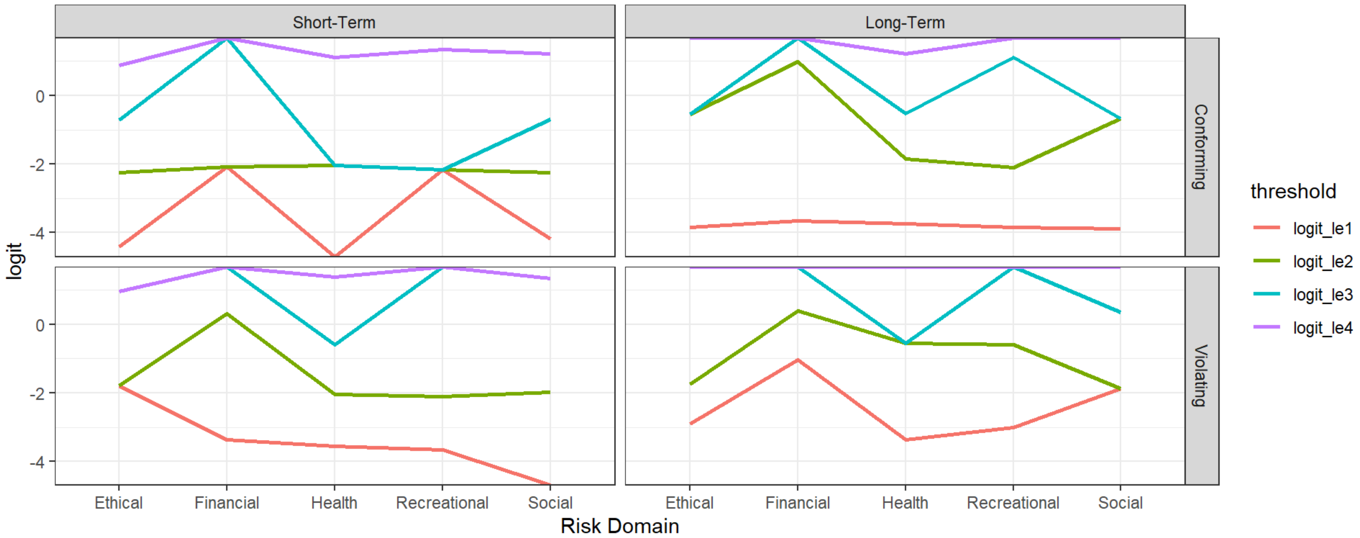
Graphically, it looks like the proportional odds assumption is violated in various places (shown by non-parallel lines). This does not affect testing whether effects exist but it does impact the effect estimates (see Long et al., 2025), which should therefore be treated with caution.

```
cum_probs <- data1 %>%
  group_by(Rel_type, Norm_type, Rt_type) %>%
  summarise(
    P_le1 = mean(At_rating <= 1),
    P_le2 = mean(At_rating <= 2),
    P_le3 = mean(At_rating <= 3),
    P_le4 = mean(At_rating <= 4)
  ) %>%
  mutate(
    logit_le1 = log(P_le1 / (1 - P_le1)),
    logit_le2 = log(P_le2 / (1 - P_le2)),
    logit_le3 = log(P_le3 / (1 - P_le3)),
    logit_le4 = log(P_le4 / (1 - P_le4))
  ) %>%
  pivot_longer(cols = starts_with("logit"), names_to = "threshold", values_to = "logit")

ggplot(cum_probs, aes(x = Rel_type, y = logit, color = threshold, group = threshold)) +
  geom_line(linewidth = 1) +
  facet_grid(Norm_type ~ Rt_type) +
  theme_bw() +
  labs(x="Relationship Context")
```


```
ggplot(cum_probs, aes(x = Norm_type, y = logit, color = threshold, group = threshold)) +
  geom_line(linewidth = 1) +
  facet_grid(Rel_type ~ Rt_type) +
  theme_bw() +
  labs(x="Norm Adherence")
```




```
ggplot(cum_probs, aes(x = Rt_type, y = logit, color = threshold, group = threshold)) +
  geom_line(linewidth = 1) +
  facet_grid(Norm_type ~ Rel_type) +
  theme_bw() +
  labs(x="Risk Domain")
```



Model output

```
summary(mdl2)
```

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula: factor(At_rating) ~ Rel_type * Norm_type * Rt_type + (Norm_type |
##     ID)
## data:    data1
##
##  link  threshold nobs  logLik    AIC      niter       max.grad cond.H
##  logit flexible  20000 -22900.83 45853.65 7576(58871) 5.19e-03 6.7e+02
##
## Random effects:
##  Groups Name               Variance Std.Dev. Corr
##  ID     (Intercept)        1.5245   1.2347
##         Norm_typeViolating 0.0834   0.2888   -0.713
## Number of groups:  ID 1000
##
## Coefficients:
##                                                          Estimate Std. Error
## Rel_typeLong-Term                                        -1.55985    0.09032
## Norm_typeViolating                                       -1.69829    0.09481
## Rt_typeFinancial                                         -2.86005    0.08906
## Rt_typeHealth                                             0.45817    0.08786
## Rt_typeRecreational                                       0.32220    0.08842
## Rt_typeSocial                                            -0.21344    0.08864
## Rel_typeLong-Term:Norm_typeViolating                      0.42321    0.12615
## Rel_typeLong-Term:Rt_typeFinancial                        0.08280    0.12283
## Rel_typeLong-Term:Rt_typeHealth                           0.67297    0.12488
## Rel_typeLong-Term:Rt_typeRecreational                    -0.78838    0.12308
## Rel_typeLong-Term:Rt_typeSocial                           0.38695    0.12552
## Norm_typeViolating:Rt_typeFinancial                       0.63689    0.12503
## Norm_typeViolating:Rt_typeHealth                          0.81686    0.12759
## Norm_typeViolating:Rt_typeRecreational                   -1.30451    0.12545
## Norm_typeViolating:Rt_typeSocial                          0.13995    0.12806
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeFinancial     0.47696    0.17339
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeHealth       -0.64659    0.17709
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeRecreational  1.26144    0.17239
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeSocial        0.74932    0.17709
##                                                          z value Pr(>|z|)
## Rel_typeLong-Term                                        -17.271  < 2e-16 ***
## Norm_typeViolating                                       -17.913  < 2e-16 ***
## Rt_typeFinancial                                         -32.115  < 2e-16 ***
## Rt_typeHealth                                              5.215 1.84e-07 ***
## Rt_typeRecreational                                        3.644 0.000268 ***
## Rt_typeSocial                                             -2.408 0.016039 *
## Rel_typeLong-Term:Norm_typeViolating                       3.355 0.000794 ***
## Rel_typeLong-Term:Rt_typeFinancial                         0.674 0.500254
## Rel_typeLong-Term:Rt_typeHealth                            5.389 7.09e-08 ***
## Rel_typeLong-Term:Rt_typeRecreational                     -6.405 1.50e-10 ***
## Rel_typeLong-Term:Rt_typeSocial                            3.083 0.002050 **
## Norm_typeViolating:Rt_typeFinancial                        5.094 3.51e-07 ***
## Norm_typeViolating:Rt_typeHealth                           6.402 1.53e-10 ***
## Norm_typeViolating:Rt_typeRecreational                   -10.399  < 2e-16 ***
## Norm_typeViolating:Rt_typeSocial                           1.093 0.274449
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeFinancial      2.751 0.005945 **
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeHealth        -3.651 0.000261 ***
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeRecreational   7.317 2.53e-13 ***
```

```
## Rel_typeLong-Term:Norm_typeViolating:Rt_typeSocial         4.231 2.32e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##     Estimate Std. Error z value
## 1|2 -5.95595    0.08883  -67.05
## 2|3 -3.67772    0.08049  -45.69
## 3|4 -1.00358    0.07619  -13.17
## 4|5  1.56482    0.07658   20.43
```

Pairwise contrasts

The pattern of results (in terms of which pairwise differences are statistically significant) matches the linear model, except for financial risk-taking in the context of long-term relationships (which is not significant here).

```
emmeans(mdl2, pairwise~Rel_type | Rt_type)
```

```
## $emmeans
## Rt_type = Ethical:
##  Rel_type    emmean     SE  df asymp.LCL asymp.UCL
##  Short-Term  1.4190 0.0600 Inf    1.3014     1.537
##  Long-Term   0.0707 0.0562 Inf   -0.0394     0.181
##
## Rt_type = Financial:
##  Rel_type    emmean     SE  df asymp.LCL asymp.UCL
##  Short-Term -1.1226 0.0559 Inf   -1.2321    -1.013
##  Long-Term  -2.1496 0.0581 Inf   -2.2635    -2.036
##
## Rt_type = Health:
##  Rel_type    emmean     SE  df asymp.LCL asymp.UCL
##  Short-Term  2.2856 0.0587 Inf    2.1705     2.401
##  Long-Term   1.2870 0.0584 Inf    1.1726     1.401
##
## Rt_type = Recreational:
##  Rel_type    emmean     SE  df asymp.LCL asymp.UCL
##  Short-Term  1.0889 0.0558 Inf    0.9796     1.198
##  Long-Term  -0.4170 0.0555 Inf   -0.5258    -0.308
##
## Rt_type = Social:
##  Rel_type    emmean     SE  df asymp.LCL asymp.UCL
##  Short-Term  1.2755 0.0578 Inf    1.1621     1.389
##  Long-Term   0.6889 0.0577 Inf    0.5758     0.802
##
## Results are averaged over the levels of: Norm_type
## Results are given on the factor (not the response) scale.
## Confidence level used: 0.95
##
## $contrasts
## Rt_type = Ethical:
##  contrast                   estimate     SE  df z.ratio p.value
##  (Short-Term) - (Long-Term)    1.348 0.0638 Inf  21.137  <.0001
##
## Rt_type = Financial:
##  contrast                   estimate     SE  df z.ratio p.value
##  (Short-Term) - (Long-Term)    1.027 0.0599 Inf  17.146  <.0001
##
## Rt_type = Health:
##  contrast                   estimate     SE  df z.ratio p.value
##  (Short-Term) - (Long-Term)    0.999 0.0627 Inf  15.936  <.0001
##
## Rt_type = Recreational:
##  contrast                   estimate     SE  df z.ratio p.value
##  (Short-Term) - (Long-Term)    1.506 0.0597 Inf  25.241  <.0001
##
## Rt_type = Social:
##  contrast                   estimate     SE  df z.ratio p.value
##  (Short-Term) - (Long-Term)    0.587 0.0623 Inf   9.422  <.0001
##
## Results are averaged over the levels of: Norm_type
## Note: contrasts are still on the factor scale
```

```
# correct p values for multiple comparisons
p_list = summary(emmeans(mdl2, pairwise~Rel_type | Rt_type)$contrasts)$p.value
round(p.adjust(p_list, method = "holm", n = length(p_list)), digits=3)
```

```
## [1] 0 0 0 0 0
```

```
emmeans(mdl2, pairwise~Norm_type | Rel_type*Rt_type)
```

```
## $emmeans
## Rel_type = Short-Term, Rt_type = Ethical:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming  2.268 0.0764 Inf     2.118     2.418
##  Violating   0.570 0.0766 Inf     0.420     0.720
##
## Rel_type = Long-Term, Rt_type = Ethical:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming  0.708 0.0748 Inf     0.562     0.855
##  Violating  -0.567 0.0664 Inf    -0.697    -0.437
##
## Rel_type = Short-Term, Rt_type = Financial:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming -0.592 0.0712 Inf    -0.732    -0.452
##  Violating  -1.653 0.0682 Inf    -1.787    -1.520
##
## Rel_type = Long-Term, Rt_type = Financial:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming -2.069 0.0727 Inf    -2.211    -1.927
##  Violating  -2.230 0.0718 Inf    -2.371    -2.090
##
## Rel_type = Short-Term, Rt_type = Health:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming  2.726 0.0746 Inf     2.580     2.873
##  Violating   1.845 0.0719 Inf     1.704     1.986
##
## Rel_type = Long-Term, Rt_type = Health:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming  1.839 0.0750 Inf     1.692     1.986
##  Violating   0.735 0.0724 Inf     0.593     0.876
##
## Rel_type = Short-Term, Rt_type = Recreational:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming  2.590 0.0752 Inf     2.443     2.738
##  Violating  -0.412 0.0660 Inf    -0.542    -0.283
##
## Rel_type = Long-Term, Rt_type = Recreational:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming  0.242 0.0702 Inf     0.104     0.380
##  Violating  -1.076 0.0688 Inf    -1.211    -0.941
##
## Rel_type = Short-Term, Rt_type = Social:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming  2.055 0.0747 Inf     1.908     2.201
##  Violating   0.496 0.0714 Inf     0.356     0.636
##
## Rel_type = Long-Term, Rt_type = Social:
##  Norm_type  emmean     SE  df asymp.LCL asymp.UCL
##  Conforming  0.882 0.0746 Inf     0.736     1.028
##  Violating   0.496 0.0707 Inf     0.357     0.635
##
## Results are given on the factor (not the response) scale.
## Confidence level used: 0.95
##
## $contrasts
```

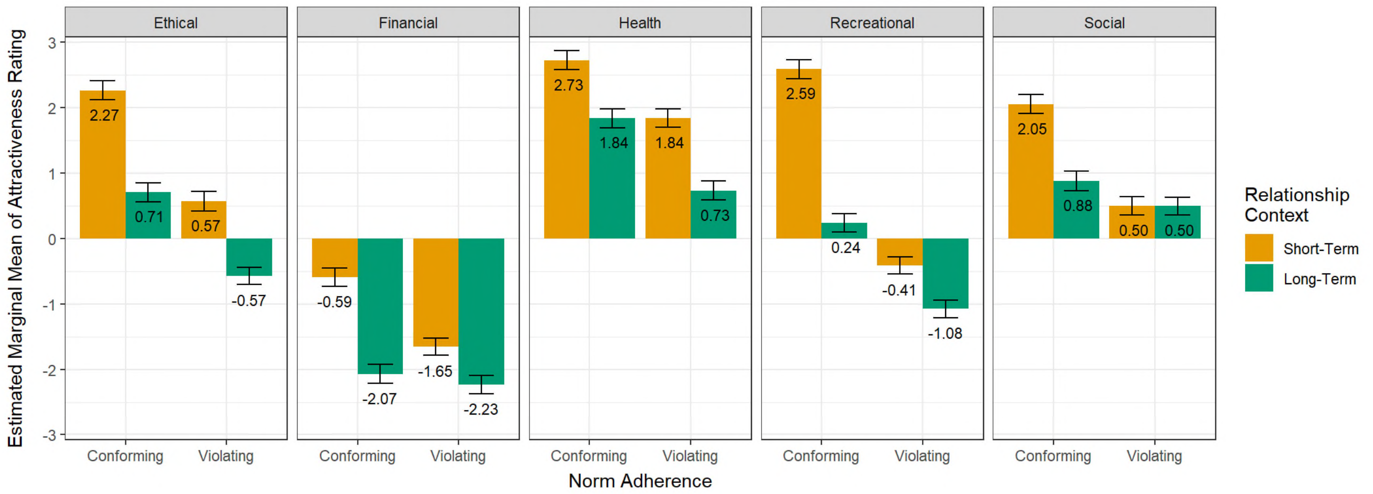
```
## Rel_type = Short-Term, Rt_type = Ethical:
##  contrast                estimate     SE  df z.ratio p.value
##  Conforming - Violating    1.698 0.0948 Inf  17.913  <.0001
##
## Rel_type = Long-Term, Rt_type = Ethical:
##  contrast                estimate     SE  df z.ratio p.value
##  Conforming - Violating    1.275 0.0859 Inf  14.841  <.0001
##
## Rel_type = Short-Term, Rt_type = Financial:
##  contrast                estimate     SE  df z.ratio p.value
##  Conforming - Violating    1.061 0.0834 Inf  12.727  <.0001
##
## Rel_type = Long-Term, Rt_type = Financial:
##  contrast                estimate     SE  df z.ratio p.value
##  Conforming - Violating    0.161 0.0857 Inf   1.881  0.0599
##
## Rel_type = Short-Term, Rt_type = Health:
##  contrast                estimate     SE  df z.ratio p.value
##  Conforming - Violating    0.881 0.0876 Inf  10.061  <.0001
##
## Rel_type = Long-Term, Rt_type = Health:
##  contrast                estimate     SE  df z.ratio p.value
##  Conforming - Violating    1.105 0.0900 Inf  12.269  <.0001
##
## Rel_type = Short-Term, Rt_type = Recreational:
##  contrast                estimate     SE  df z.ratio p.value
##  Conforming - Violating    3.003 0.0871 Inf  34.462  <.0001
##
## Rel_type = Long-Term, Rt_type = Recreational:
##  contrast                estimate     SE  df z.ratio p.value
##  Conforming - Violating    1.318 0.0838 Inf  15.738  <.0001
##
## Rel_type = Short-Term, Rt_type = Social:
##  contrast                estimate     SE  df z.ratio p.value
##  Conforming - Violating    1.558 0.0892 Inf  17.463  <.0001
##
## Rel_type = Long-Term, Rt_type = Social:
##  contrast                estimate     SE  df z.ratio p.value
##  Conforming - Violating    0.386 0.0884 Inf   4.363  <.0001
##
## Note: contrasts are still on the factor scale
```

```
# correct p values for multiple comparisons
p_list = summary(emmeans(mdl2, pairwise~Norm_type | Rel_type*Rt_type)$contrasts)$p.value
round(p.adjust(p_list, method = "holm", n = length(p_list)), digits=3)  # all sig except L-T Fin.
```

```
##  [1] 0.00 0.00 0.00 0.06 0.00 0.00 0.00 0.00 0.00 0.00
```

Figure

```
fig2 = ggplot(as.data.frame(emmeans(mdl2, ~ Rel_type*Rt_type*Norm_type)), aes(x=Norm_type, y=
emmean, fill=Rel_type)) +
    facet_grid(.~Rt_type) +
  geom_col(position="dodge") +
  geom_errorbar(aes(ymin=asymp.LCL, ymax=asymp.UCL), colour="black", position=position_dodge
(width=0.9), width=.5) +
  geom_text(aes(label=format(round(emmean, 2), nsmall = 2)), position=position_dodge(width=.
9), vjust=2.5, size=3) +
  theme_bw() +
  scale_fill_manual(values=c("#e69f00", "#009e73")) +
  labs(x="Norm Adherence", y="Estimated Marginal Mean of Attractiveness Rating", fill="Relati
onship\nContext") +
  coord_cartesian(ylim=c(-2.8,2.8)) +
  theme(axis.title.y = element_text(margin = margin(r = 10)), axis.title.x = element_text(mar
gin = margin(t = 5)))
fig2
```



References

Long, Y., Wiegers, E. J. A., Jacobs, B. C., Steyerberg, E. W., & Zwet, E. W. van. (2025). Role of the proportional odds assumption for the analysis of ordinal outcomes in neurologic trials. *Neurology*, *105*(8), e214146. https://doi.org/10.1212/WNL.0000000000214146 (https://doi.org/10.1212/WNL.0000000000214146)

Sylwester, K., & Pawłowski, B. (2011). Daring to be darling: Attractiveness of risk takers as partners in long-and short-term sexual relationships. *Sex Roles*, *64*(9), 695-706. https://doi.org/10.1007/s11199-010-9790-6 (https://doi.org/10.1007/s11199-010-9790-6)