Supplemental Materials

Study 1

Figure 1. Table of results for only the "competence" study designs in Study 1

	SIM Effect		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-2.02	-2.25 – -1.80	**<0.001**
Competence	-0.09	-0.34 – 0.15	0.464
Active	2.12	1.90 – 2.33	**<0.001**
Intermediate	1.98	1.77 – 2.20	**<0.001**
Competence*Active	0.50	0.24 – 0.77	**<0.001**
Competence*Intermediate	0.33	0.08 – 0.58	**0.009**
Random Effects			
σ^2	0.67		
$\tau_{00\ Study}$	0.02		
$\tau_{11\ Study.zscore\_comb}$	0.00		
$\rho_{01\ Study}$	1.00		
N_{Study}	6		
Observations	3560		
Marginal R^2 / Conditional R^2	0.338 / NA		

Figure 2. Graph of results for only the “competence” study designs in Study 1

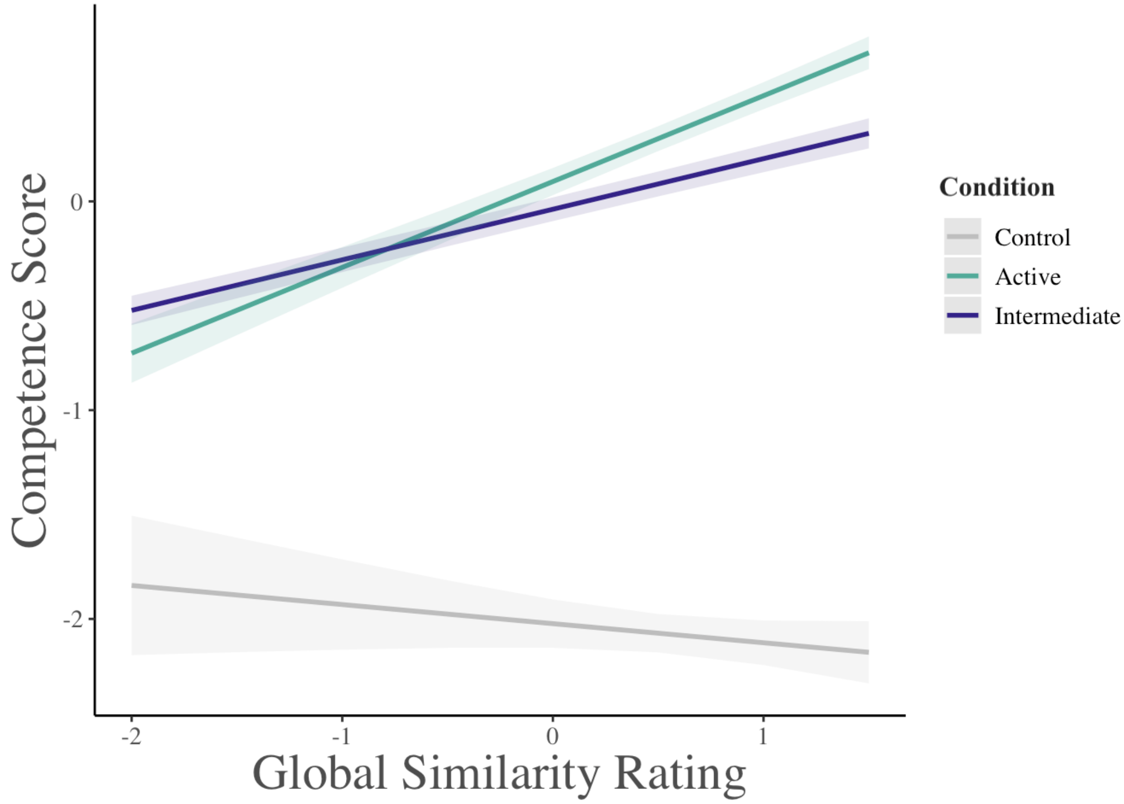


Figure 3. Table of results for only the “similarity” study designs in Study 1

	SIM Effect		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.10	-0.22 – 0.03	0.138
Similarity	-0.05	-0.16 – 0.06	0.357
Active	0.15	0.05 – 0.26	**0.005**
Intermediate	0.31	0.08 – 0.53	**0.007**
Similarity*Active	0.16	0.05 – 0.27	**0.006**
Similarity*Intermediate	0.25	0.06 – 0.44	**0.012**
Random Effects			
σ^2	0.89		
$\tau_{00\ \text{Study}}$	0.01		
$\tau_{11\ \text{Study.zscore\_comb}}$	0.00		
$\rho_{01\ \text{Study}}$	0.12		
ICC	0.02		
N_{Study}	9		
Observations	4093		
Marginal R^2 / Conditional R^2	0.012 / 0.029		

Figure 4. Graph of results for only the “similarity” study designs in Study 1

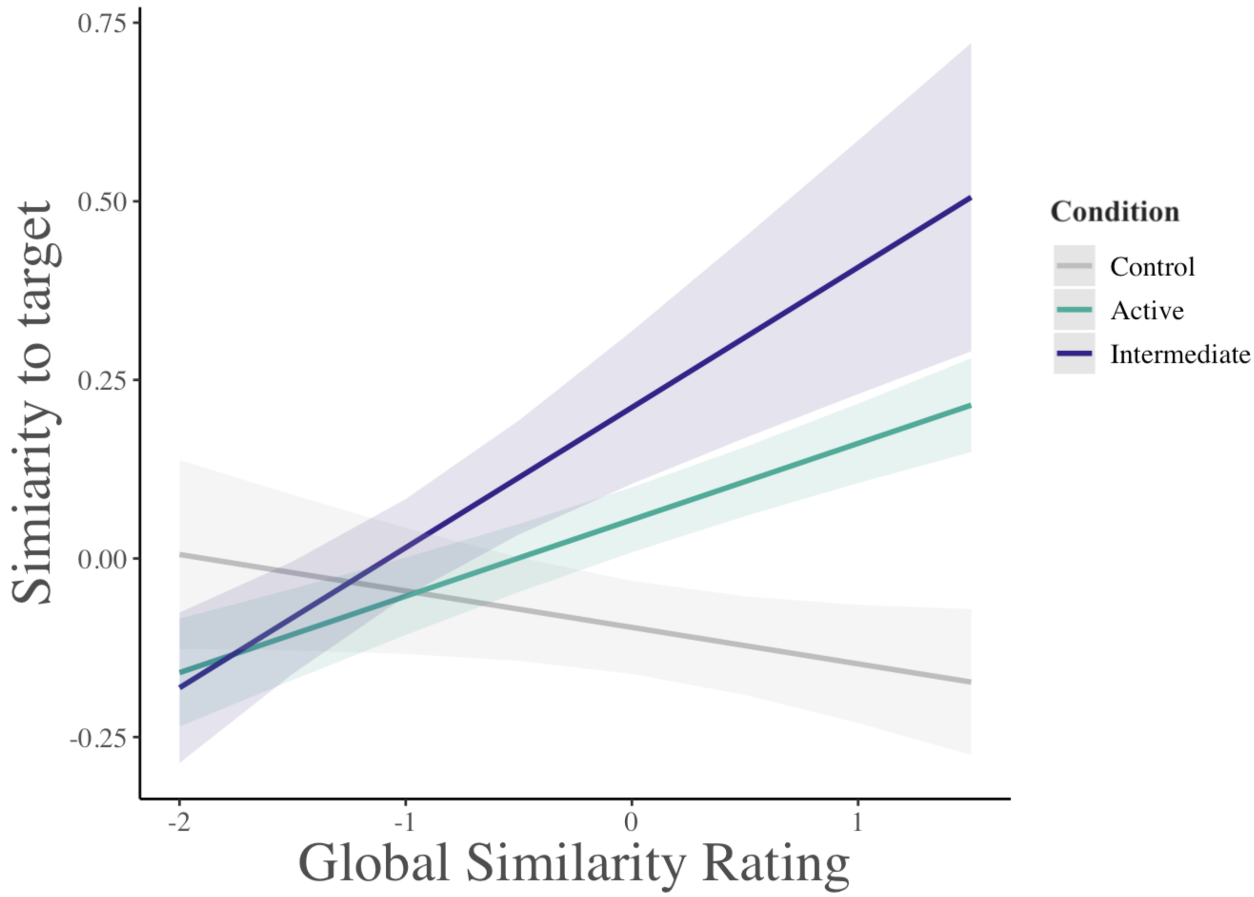


Figure 5. Analyses for each similarity measure used in Study 1

	Emotional Closeness and SIM		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.60	-0.78 – -0.43	**<0.001**
Emotional Closeness	-0.22	-0.40 – -0.05	**0.010**
Active	0.69	0.60 – 0.78	**<0.001**
Intermediate	0.54	0.44 – 0.65	**<0.001**
Closeness*Active	0.43	0.35 – 0.51	**<0.001**
Closeness*Intermediate	0.30	0.21 – 0.38	**<0.001**
Random Effects			
σ^2	0.84		
$\tau_{00\ \mathrm{Study}}$	0.06		
$\tau_{00\ \mathrm{design}}$	0.00		
$\tau_{11\ \mathrm{Study.zscore\_e}}$	0.00		
$\tau_{11\ \mathrm{design.zscore\_e}}$	0.01		
$\rho_{01\ \mathrm{Study}}$	1.00		
$\rho_{01\ \mathrm{design}}$	-1.00		
N_{Study}	15		
N_{design}	2		
Observations	7653		
Marginal R^2 / Conditional R^2	0.083 / NA		

	Similarity and SIM		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.61	-0.82 – -0.39	**<0.001**
Similarity	-0.18	-0.41 – 0.06	0.136
Active	0.66	0.57 – 0.75	**<0.001**
Intermediate	0.54	0.44 – 0.65	**<0.001**
Similarity*Active	0.43	0.34 – 0.52	**<0.001**
Similarity*Intermediate	0.31	0.21 – 0.41	**<0.001**
Random Effects			
σ^2	0.83		
$\tau_{00\ \mathrm{Study}}$	0.06		
$\tau_{00\ \mathrm{design}}$	0.01		
$\tau_{11\ \mathrm{Study.zscore\_s}}$	0.00		
$\tau_{11\ \mathrm{design.zscore\_s}}$	0.02		
$\rho_{01\ \mathrm{Study}}$	0.91		
$\rho_{01\ \mathrm{design}}$	-1.00		
N_{Study}	15		
N_{design}	2		
Observations	7653		
Marginal R^2 / Conditional R^2	0.097 / NA		

	IOS and SIM		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.55	-0.73 – -0.37	**<0.001**
IOS	-0.25	-0.33 – -0.17	**<0.001**
Active	0.65	0.56 – 0.74	**<0.001**
Intermediate	0.53	0.42 – 0.63	**<0.001**
IOS*Active	0.45	0.36 – 0.53	**<0.001**
IOS*Intermediate	0.40	0.31 – 0.49	**<0.001**
Random Effects			
σ^2	0.84		
$\tau_{00\ Study}$	0.06		
$\tau_{00\ design}$	0.01		
$\tau_{11\ Study.zscore\_ios}$	0.00		
$\tau_{11\ design.zscore\_ios}$	0.00		
$\rho_{01\ Study}$	1.00		
$\rho_{01\ design}$	-1.00		
N_{Study}	15		
N_{design}	2		
Observations	7653		
Marginal R^2 / Conditional R^2	0.087 / NA		

Study 2

Figure 6. Table of results from Study 2 Pilot

Pilot Results

Predictor	df_{Num}	df_{Den}	SS_{Num}	SS_{Den}	F	p	η^2_g
condition	2	12	199.14	2534.35	0.47	.635	.07

Figure 7. Graph of results from Study 2 Pilot

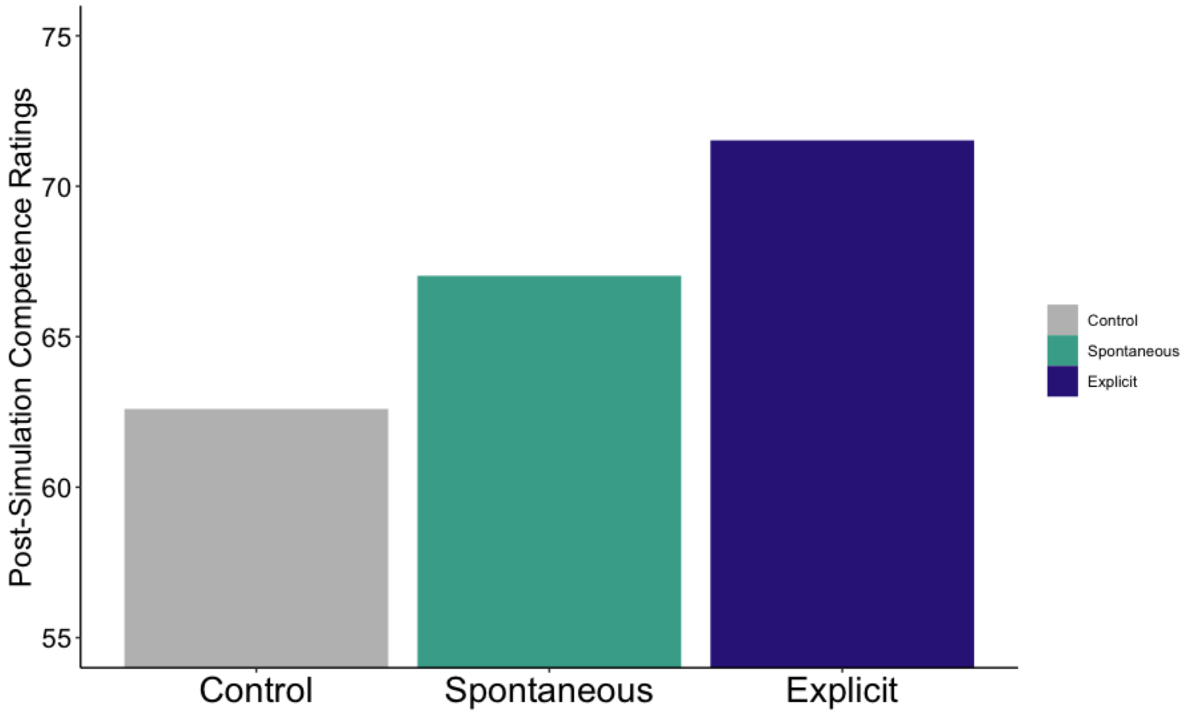


Figure 8. List of competence traits used in all studies

Capable
Efficient
Qualified
Skilled
Intelligent
Assertive
Confident
Accomplished

Study 3

AW Main Effect, Regardless of Condition

```
m<-lmer( scale(eval) ~ scale(SE) + novel + scale(desirability) + ( scale(SE) + novel |
subID) + ( 1 | trait), fullDf, control=lmerControl(optimizer="bobyqa",
                                    optCtrl=list(maxfun=2e5)))
#tab_model(m, show.stat=T, show.r2 = T, show.se = T,pred.labels = c("Intercept",
"AW","Novelty","Desirability"), string.pred = c("Fixed Effects"), string.stat = "t",
digits = 3, emph.p = F)
mp <- model_parameters(m)
print_md(mp)
```

Fixed Effects

Parameter	Coefficient	SE	95% CI	t(36432)	p
(Intercept)	-3.68e-03	0.04	(-0.07, 0.07)	-0.10	0.920
SE	0.08	0.02	(0.05, 0.12)	5.10	< .001
novel	0.01	0.01	(-8.44e-03, 0.03)	1.15	0.251
desirability	0.13	0.02	(0.09, 0.16)	6.74	< .001

Random Effects

Parameter	Coefficient
SD (Intercept: subID)	0.48
SD (Intercept: trait)	0.21
SD (scale(SE): subID)	0.09
SD (novel: subID)	0.07
Cor (Intercept~scale(SE): subID)	0.20
Cor (Intercept~novel: subID)	1.93e-05
Cor (scale(SE)~novel: subID)	0.35
SD (Residual)	0.83

```
data.frame(r2beta(m))

                Effect          F v1    v2         ncp          Rsq     upper.CL
1                Model 466.265903  3 36443 1398.797708 3.696436e-02 0.0408716169
4 scale(desirability) 580.737999  1 36443  580.737999 1.568556e-02 0.0183050100
2            scale(SE) 254.110544  1 36443  254.110544 6.924538e-03 0.0087205155
3                novel   1.493201  1 36443    1.493201 4.097191e-05 0.0002777886
      lower.CL
1 3.333710e-02
4 1.326274e-02
2 5.333048e-03
3 1.198310e-07
```

Zero Order Effects

```
m<-lmer( scale(eval) ~ scale(SE) + ( scale(SE) | subID) + ( 1 | trait), fullDf,
control=lmerControl(optimizer="bobyqa",
                                optCtrl=list(maxfun=2e5)))
#tab_model(m, show.stat=T, show.r2 = T, show.se = T,pred.labels = c("Intercept", "AW"),
string.pred = c("Fixed Effects"), string.stat = "t", digits = 3, emph.p = F)
mp <- model_parameters(m)
print_md(mp)
```

Fixed Effects

Parameter	Coefficient	SE	95% CI	t(36437)	p
(Intercept)	1.45e-03	0.04	(-0.07, 0.08)	0.04	0.969
SE	0.11	0.02	(0.08, 0.14)	6.81	< .001

Random Effects

Parameter	Coefficient
SD (Intercept: subID)	0.48
SD (Intercept: trait)	0.24
SD (scale(SE): subID)	0.09
Cor (Intercept~scale(SE): subID)	0.22
SD (Residual)	0.83

```
data.frame(r2beta(m))

     Effect        F v1    v2      ncp        Rsq   upper.CL   lower.CL
1     Model 521.8231  1 36443 521.8231 0.01411675 0.01661226 0.01181927
2 scale(SE) 521.8231  1 36443 521.8231 0.01411675 0.01661226 0.01181927
```

AW Between Conditions

Similarity-to-others predicts self-evaluations more than similarity-to-self predicts other-evaluations.

Fixed Effects

Parameter	Coefficient	SE	95% CI	t(36428)	p
(Intercept)	-0.01	0.05	(-0.11, 0.09)	-0.22	0.828
SE	0.11	0.02	(0.07, 0.15)	5.72	< .001
Condition [SO]	0.02	0.07	(-0.11, 0.15)	0.23	0.820
novel	0.01	0.01	(-8.30e-03, 0.03)	1.15	0.251
desirability	0.14	0.02	(0.10, 0.18)	7.75	< .001
SE × Condition [SO]	-0.05	0.02	(-0.10, -0.01)	-2.58	0.010

Random Effects

Parameter	Coefficient
SD (Intercept: subID)	0.48
SD (Intercept: trait)	0.26
SD (scale(SE): subID)	0.09
SD (novel: subID)	0.07
SD (ConditionSO: trait)	0.22
Cor (Intercept~scale(SE): subID)	0.20
Cor (Intercept~novel: subID)	0.01
Cor (Intercept~ConditionSO: trait)	-0.67
Cor (scale(SE)~novel: subID)	0.46
SD (Residual)	0.82

Zero-Order Effects

```
m<-lmer( scale(eval) ~ scale(SE)*Condition + ( scale(SE) | subID) + ( 1 | trait), fullDf)
#tab_model(m, show.stat=T, show.r2 = T, show.se = T, pred.labels = c("Intercept",
"AW","Self-then-Other", "AW*Self-then-Other"), string.pred = c("Fixed Effects"),
```

```
string.stat = "t", digits = 3, emph.p = F)
mp <- model_parameters(m)
print_md(mp)
```

 # Fixed Effects

Parameter	Coefficient	SE	95% CI	t(36435)	p
(Intercept)	-5.92e-03	0.05	(-0.10, 0.09)	-0.12	0.904
SE	0.13	0.02	(0.10, 0.17)	7.72	< .001
Condition [SO]	0.01	0.06	(-0.11, 0.14)	0.23	0.817
SE × Condition [SO]	-0.05	0.01	(-0.08, -0.02)	-3.63	< .001

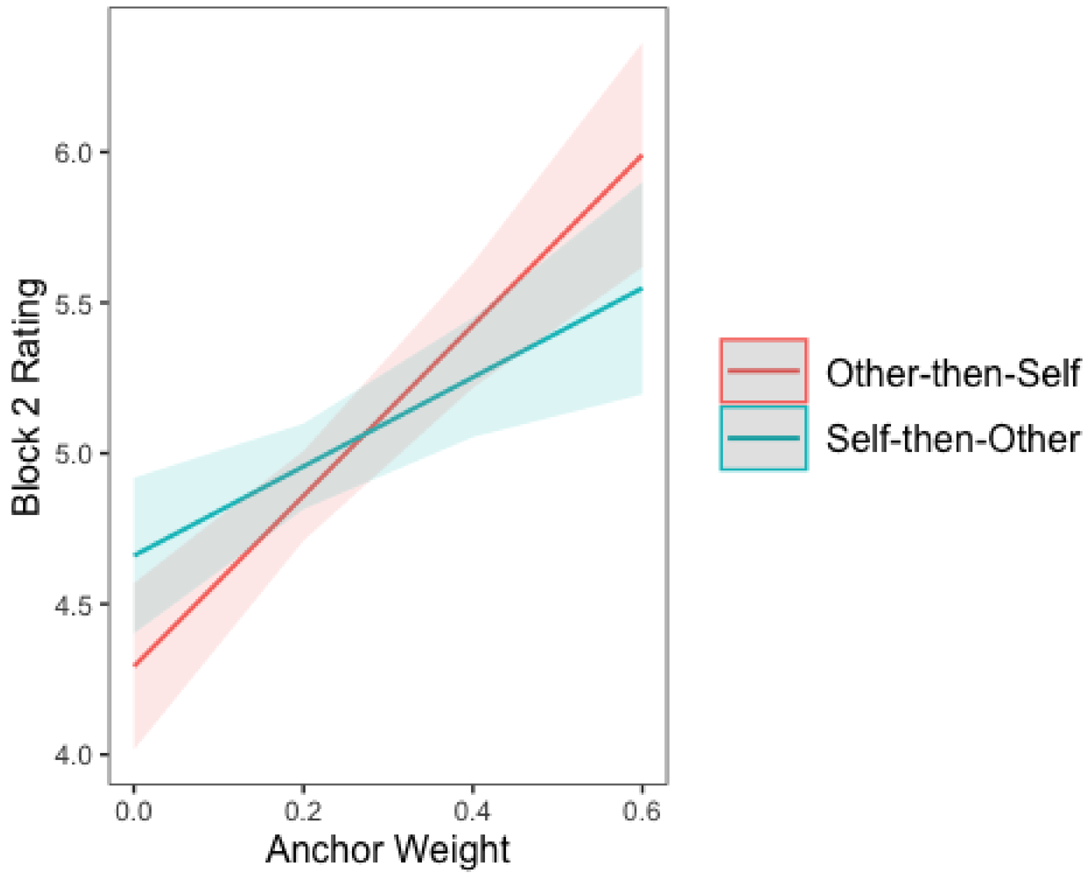
 # Random Effects

Parameter	Coefficient
SD (Intercept: subID)	0.48
SD (Intercept: trait)	0.24
SD (scale(SE): subID)	0.08
Cor (Intercept~scale(SE): subID)	0.24
SD (Residual)	0.83

Plot

```
m<-lmer( eval ~ SE*Condition + novel + desirability + ( SE + novel | subID) + ( Condition
| trait), fullDf)
ggpredict(m, c("SE","Condition")) %>% plot(show.title=F) + xlab("Anchor Weight") +
ylab("Block 2 Rating") +
scale_color_discrete(labels=c("Other-then-Self","Self-then-Other")) + jtools::theme_apa()

Scale for colour is already present.
Adding another scale for colour, which will replace the existing scale.
```



Simple Effects Self-Other:

```
m<-lmer( scale(eval) ~ scale(SE) + novel + scale(desirability) + ( scale(SE) + novel |
subID) + (1 | trait), SOdf)
#tab_model(m, show.stat=T, show.r2 = T, show.se = T, pred.labels = c("Intercept",
"AW","Novel", "Desirability"), string.pred = c("Fixed Effects"), string.stat = "t",
digits = 3, emph.p = F)
mp <- model_parameters(m)
print_md(mp)
```

 # Fixed Effects

Parameter	Coefficient	SE	95% CI	t(17071)	p
(Intercept)	-5.50e-03	0.05	(-0.10, 0.09)	-0.12	0.906
SE	0.05	0.02	(9.18e-03, 0.08)	2.44	0.015
novel	0.01	0.01	(-0.02, 0.04)	0.81	0.419
desirability	0.15	0.02	(0.12, 0.19)	8.26	< .001

 # Random Effects

Parameter	Coefficient
SD (Intercept: trait)	0.19
SD (Intercept: subID)	0.46
SD (scale(SE): subID)	0.08
SD (novel: subID)	0.05

Parameter	Coefficient
Cor (Intercept~scale(SE): subID)	0.20
Cor (Intercept~novel: subID)	0.11
Cor (scale(SE)~novel: subID)	0.75
SD (Residual)	0.84

```
data.frame(r2beta(m))
```

```
               Effect           F v1    v2         ncp          Rsq
1               Model 209.6801707  3 17082 629.0405120 3.551686e-02
4 scale(desirability) 388.5492609  1 17082 388.5492609 2.224024e-02
2           scale(SE)  35.7591001  1 17082  35.7591001 2.089006e-03
3               novel   0.6356262  1 17082   0.6356262 3.720891e-05
      upper.CL     lower.CL
1 0.0412220786 3.041208e-02
4 0.0267917366 1.809595e-02
2 0.0036787168 9.449301e-04
3 0.0004459697 1.085477e-07
```

Zero-Order Effect

```
m<-lmer( scale(eval) ~ scale(SE) + ( scale(SE) | subID) + (1 | trait), SOdf)
```

```
Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
Model failed to converge with max|grad| = 0.00232293 (tol = 0.002, component 1)
```

```
#tab_model(m, show.stat=T, show.r2 = T, show.se = T, pred.labels = c("Intercept", "AW"),
string.pred = c("Fixed Effects"), string.stat = "t", digits = 3, emph.p = F)
mp <- model_parameters(m)
print_md(mp)
```

 # Fixed Effects

Parameter	Coefficient	SE	95% CI	t(17076)	p
(Intercept)	-9.13e-04	0.05	(-0.10, 0.09)	-0.02	0.985
SE	0.11	0.02	(0.07, 0.15)	5.23	< .001

 # Random Effects

Parameter	Coefficient
SD (Intercept: trait)	0.25
SD (Intercept: subID)	0.47
SD (scale(SE): subID)	0.08
Cor (Intercept~scale(SE): subID)	0.25
SD (Residual)	0.84

```
data.frame(r2beta(m))
```

```
     Effect        F v1    v2      ncp        Rsq   upper.CL    lower.CL
1     Model 221.1902  1 17082 221.1902 0.01278321 0.01633183 0.009659577
2 scale(SE) 221.1902  1 17082 221.1902 0.01278321 0.01633183 0.009659577
```

Simple Effects Other-Self:

```
m<-lmer( scale(eval) ~ scale(SE) + novel + scale(desirability) + ( scale(SE) + novel |
subID) + (1 | trait), OSdf)

Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
Model failed to converge with max|grad| = 0.0022124 (tol = 0.002, component 1)

#tab_model(m, show.stat=T, show.r2 = T, show.se = T, pred.labels = c("Intercept",
"AW","Novel", "Desirability"), string.pred = c("Fixed Effects"), string.stat = "t",
digits = 3, emph.p = F)
mp <- model_parameters(m)
print_md(mp)
```

 # Fixed Effects

Parameter	Coefficient	SE	95% CI	t(19349)	p
(Intercept)	-1.11e-03	0.05	(-0.10, 0.10)	-0.02	0.983
SE	0.11	0.02	(0.07, 0.16)	5.44	< .001
novel	9.86e-03	0.01	(-0.02, 0.04)	0.69	0.489
desirability	0.11	0.02	(0.06, 0.15)	4.40	< .001

 # Random Effects

Parameter	Coefficient
SD (Intercept: trait)	0.27
SD (Intercept: subID)	0.50
SD (scale(SE): subID)	0.09
SD (novel: subID)	0.08
Cor (Intercept~scale(SE): subID)	0.20
Cor (Intercept~novel: subID)	-0.05
Cor (scale(SE)~novel: subID)	0.33
SD (Residual)	0.81

```
data.frame(r2beta(m))

               Effect           F v1    v2         ncp          Rsq
1               Model 268.8673752  3 19360 806.6021255 3.999693e-02
2           scale(SE) 249.8144304  1 19360 249.8144304 1.273926e-02
4 scale(desirability) 216.4300033  1 19360 216.4300033 1.105564e-02
3               novel   0.5610466  1 19360   0.5610466 2.897884e-05
      upper.CL     lower.CL
1 0.0456133798 3.490147e-02
2 0.0160553765 9.798203e-03
4 0.0141653258 8.323862e-03
3 0.0003802684 8.889443e-08
```

Zero-Order Effect

```
m<-lmer( scale(eval) ~ scale(SE) + ( scale(SE) | subID) + (1 | trait), OSdf)

Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
Model failed to converge with max|grad| = 0.00459576 (tol = 0.002, component 1)
```

```
#tab_model(m, show.stat=T, show.r2 = T, show.se = T, pred.labels = c("Intercept", "AW"),
string.pred = c("Fixed Effects"), string.stat = "t", digits = 3, emph.p = F)
mp <- model_parameters(m)
print_md(mp)
```

 # Fixed Effects

Parameter	Coefficient	SE	95% CI	t(19354)	p
(Intercept)	3.33e-03	0.05	(-0.10, 0.11)	0.06	0.949
SE	0.13	0.02	(0.09, 0.17)	6.79	< .001

 # Random Effects

Parameter	Coefficient
SD (Intercept: trait)	0.29
SD (Intercept: subID)	0.50
SD (scale(SE): subID)	0.09
Cor (Intercept~scale(SE): subID)	0.23
SD (Residual)	0.81

```
data.frame(r2beta(m))

     Effect        F v1    v2      ncp        Rsq   upper.CL   lower.CL
1     Model 416.1752  1 19360 416.1752 0.02104427 0.02520383 0.01724596
2 scale(SE) 416.1752  1 19360 416.1752 0.02104427 0.02520383 0.01724596
```

Effect of Similarity-Estimate for Novel Traits

The effect holds for initially evaluated traits as well as novel traits, and then secondarily it may even be stronger for novel traits

```
m<-lmer( scale(eval) ~ scale(SE)*Condition*novel + scale(desirability) + ( scale(SE) +
novel | subID) + ( Condition | trait), fullDf)

Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
Model failed to converge with max|grad| = 0.00238581 (tol = 0.002, component 1)

#tab_model(m, show.stat=T, show.r2 = T, show.se = T, pred.labels = c("Intercept",
"AW","Self-then-Other","Novel", "Desirability", "AW*Self-then-Other"), string.pred =
c("Fixed Effects"), string.stat = "t", digits = 3, emph.p = F)
mp <- model_parameters(m)
print_md(mp)
```

 # Fixed Effects

Parameter	Coefficient	SE	95% CI	t(36425)	p
(Intercept)	-9.71e-03	0.05	(-0.11, 0.09)	-0.19	0.847
SE	0.11	0.02	(0.07, 0.15)	5.16	< .001
Condition [SO]	0.01	0.07	(-0.12, 0.14)	0.19	0.848
novel	9.90e-03	0.01	(-0.02, 0.04)	0.71	0.480
desirability	0.14	0.02	(0.10, 0.18)	7.74	< .001

Parameter	Coefficient	SE	95% CI	t(36425)	p
SE × Condition [SO]	-0.04	0.02	(-0.08, 6.22e-03)	-1.69	0.091
SE × novel	8.96e-03	0.01	(-0.01, 0.03)	0.74	0.458
Condition [SO] × novel	3.27e-03	0.02	(-0.04, 0.04)	0.16	0.871
(SE × Condition [SO]) × novel	-0.03	0.02	(-0.07, 1.31e-03)	-1.89	0.059

 # Random Effects

Parameter	Coefficient
SD (Intercept: subID)	0.48
SD (Intercept: trait)	0.26
SD (scale(SE): subID)	0.09
SD (novel: subID)	0.07
SD (ConditionSO: trait)	0.22
Cor (Intercept~scale(SE): subID)	0.20
Cor (Intercept~novel: subID)	0.01
Cor (Intercept~ConditionSO: trait)	-0.67
Cor (scale(SE)~novel: subID)	0.46
SD (Residual)	0.82

```
data.frame(r2beta(m))
```

```
                       Effect            F v1    v2          ncp          Rsq
1                       Model 208.37855878  8 36443 1.667028e+03 4.374251e-02
5         scale(desirability) 702.64984195  1 36443 7.026498e+02 1.891607e-02
2                   scale(SE) 135.64270508  1 36443 1.356427e+02 3.708249e-03
6       scale(SE):ConditionSO   9.31478588  1 36443 9.314786e+00 2.555335e-04
9 scale(SE):ConditionSO:novel   2.98838798  1 36443 2.988388e+00 8.199498e-05
3                 ConditionSO   1.00493751  1 36443 1.004938e+00 2.757484e-05
4                       novel   0.55718547  1 36443 5.571855e-01 1.528900e-05
7             scale(SE):novel   0.45777919  1 36443 4.577792e-01 1.256135e-05
8           ConditionSO:novel   0.02803109  1 36443 2.803109e-02 7.691757e-07
      upper.CL     lower.CL
1 0.0480685631 3.994014e-02
5 0.0217702418 1.625569e-02
2 0.0050564352 2.567474e-03
6 0.0006889208 3.274020e-05
9 0.0003732588 5.281112e-07
3 0.0002408806 7.359168e-08
4 0.0002016632 4.704183e-08
7 0.0001918488 4.259166e-08
8 0.0001416751 2.771453e-08
```

Zero-Order Effect

```
m<-lmer( scale(eval) ~ scale(SE)*Condition*novel + ( scale(SE) + novel | subID) + (
Condition | trait), fullDf)

Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
Model failed to converge with max|grad| = 0.00909104 (tol = 0.002, component 1)
```

```r
#tab_model(m, show.stat=T, show.r2 = T, show.se = T, pred.labels = c("Intercept",
"AW","Self-then-Other","Novel", "Desirability", "AW*Self-then-Other"), string.pred =
c("Fixed Effects"), string.stat = "t", digits = 3, emph.p = F)
mp <- model_parameters(m)
print_md(mp)
```

 # Fixed Effects

Parameter	Coefficient	SE	95% CI	t(36426)	p
(Intercept)	-0.01	0.05	(-0.11, 0.09)	-0.27	0.791
SE	0.15	0.02	(0.10, 0.19)	6.98	< .001
Condition [SO]	0.01	0.07	(-0.12, 0.14)	0.21	0.836
novel	0.02	0.01	(-9.86e-03, 0.05)	1.26	0.209
SE × Condition [SO]	-0.03	0.02	(-0.07, 0.02)	-1.13	0.258
SE × novel	8.48e-03	0.01	(-0.02, 0.03)	0.70	0.483
Condition [SO] × novel	2.61e-03	0.02	(-0.04, 0.04)	0.13	0.897
(SE × Condition [SO]) × novel	-0.03	0.02	(-0.07, 1.15e-03)	-1.90	0.058

 # Random Effects

Parameter	Coefficient
SD (Intercept: subID)	0.48
SD (Intercept: trait)	0.28
SD (scale(SE): subID)	0.09
SD (novel: subID)	0.07
SD (ConditionSO: trait)	0.22
Cor (Intercept~scale(SE): subID)	0.21
Cor (Intercept~novel: subID)	0.01
Cor (Intercept~ConditionSO: trait)	-0.52
Cor (scale(SE)~novel: subID)	0.46
SD (Residual)	0.82

```r
data.frame(r2beta(m))
```

```
                        Effect            F v1    v2          ncp          Rsq
1                        Model 107.86602861  7 36443 755.06220029 2.029843e-02
2                    scale(SE) 257.62429160  1 36443 257.62429160 7.019616e-03
5        scale(SE):ConditionSO   4.24785686  1 36443   4.24785686 1.165481e-04
8  scale(SE):ConditionSO:novel   2.98807469  1 36443   2.98807469 8.198638e-05
4                        novel   1.75387265  1 36443   1.75387265 4.812415e-05
3                  ConditionSO   1.17541638  1 36443   1.17541638 3.225252e-05
6              scale(SE):novel   0.40559655  1 36443   0.40559655 1.112949e-05
7            ConditionSO:novel   0.01769714  1 36443   0.01769714 4.856114e-07
      upper.CL     lower.CL
1 0.0234087213 1.769643e-02
2 0.0088269347 5.416698e-03
5 0.0004435204 1.760691e-06
8 0.0003732404 5.279489e-07
4 0.0002959356 1.554075e-07
```

```
3 0.0002542919 8.725453e-08
6 0.0001864790 4.042656e-08
7 0.0001402729 2.742961e-08
```

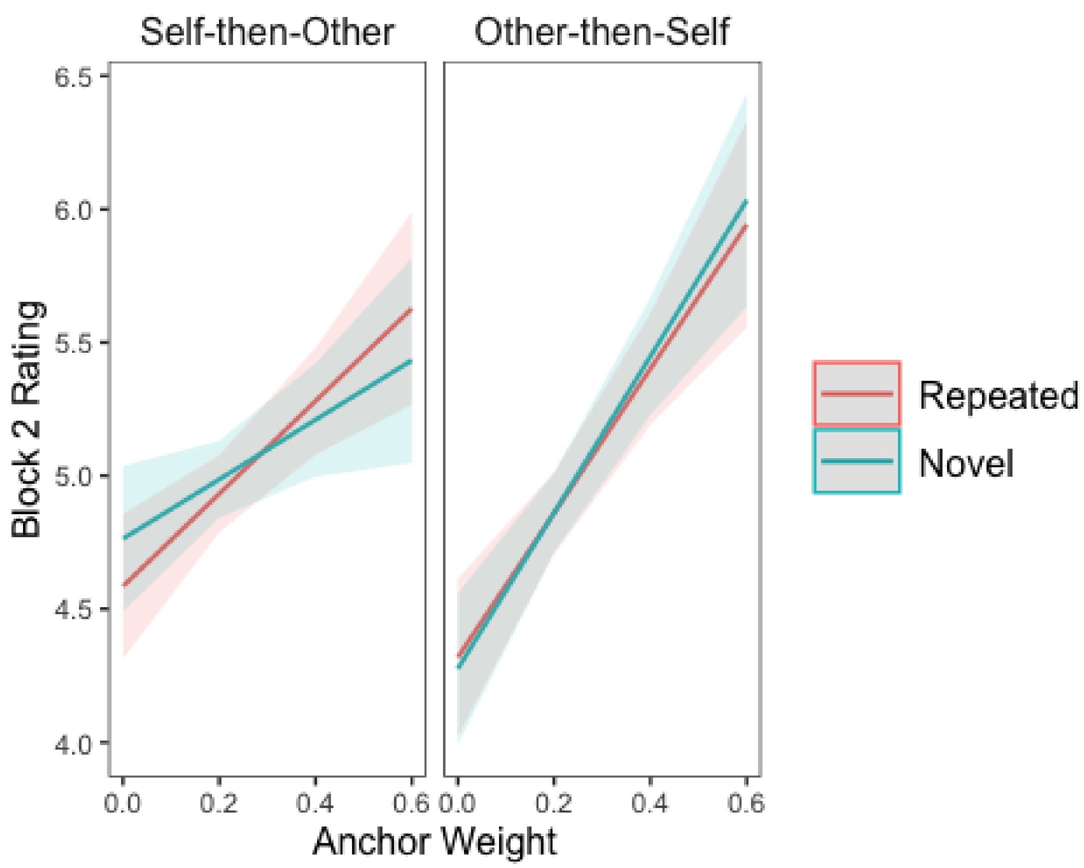
Plot

```
m<-lmer( eval ~ SE*ConditionRENAME*novel + desirability + ( SE + novel | subID) + ( ConditionRENAME | trait), fullDf)

Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
Model failed to converge with max|grad| = 0.00242131 (tol = 0.002, component 1)

ggpredict(m, c("SE","novel","ConditionRENAME")) %>% plot(show.title=F) + xlab("Anchor Weight") + ylab("Block 2 Rating") + scale_color_discrete(labels=c("Repeated","Novel")) + jtools::theme_apa()

Scale for colour is already present.
Adding another scale for colour, which will replace the existing scale.
```



Simple Effects Self-Other:

```
m<-lmer( scale(eval) ~ scale(SE) * novel + scale(desirability) + ( scale(SE) + novel | subID) + (1 | trait), SOdf)
#tab_model(m, show.stat=T, show.r2 = T, show.se = T, pred.labels = c("Intercept", "AW","Novel", "Desirability", "AW*Novel"), string.pred = c("Fixed Effects"), string.stat = "t", digits = 3, emph.p = F)
mp <- model_parameters(m)
print_md(mp)
```

Fixed Effects

Parameter	Coefficient	SE	95% CI	t(17070)	p
(Intercept)	-6.08e-03	0.05	(-0.10, 0.09)	-0.13	0.896
SE	0.06	0.02	(0.02, 0.10)	2.83	0.005
novel	0.01	0.01	(-0.02, 0.04)	0.77	0.443
desirability	0.15	0.02	(0.12, 0.19)	8.24	< .001
SE × novel	-0.02	0.01	(-0.05, 2.35e-03)	-1.79	0.074

Random Effects

Parameter	Coefficient
SD (Intercept: trait)	0.19
SD (Intercept: subID)	0.46
SD (scale(SE): subID)	0.08
SD (novel: subID)	0.05
Cor (Intercept~scale(SE): subID)	0.20
Cor (Intercept~novel: subID)	0.11
Cor (scale(SE)~novel: subID)	0.76
SD (Residual)	0.84

```
data.frame(r2beta(m))

               Effect          F v1    v2        ncp          Rsq     upper.CL
1               Model 158.112158  4 17082 632.448633 3.570242e-02 0.0414762073
4 scale(desirability) 387.352171  1 17082 387.352171 2.217324e-02 0.0267186144
2           scale(SE)  34.305992  1 17082  34.305992 2.004287e-03 0.0035662191
5     scale(SE):novel   2.717465  1 17082   2.717465 1.590582e-04 0.0007618537
3               novel   0.574269  1 17082   0.574269 3.361724e-05 0.0004336665
      lower.CL
1 3.063736e-02
4 1.803519e-02
2 8.881559e-04
5 8.629886e-07
3 1.020900e-07
```

Zero-Order Effects

```
m<-lmer( scale(eval) ~ scale(SE) * novel + ( scale(SE) + novel | subID) + (1 | trait),
SOdf)

Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
Model failed to converge with max|grad| = 0.00304642 (tol = 0.002, component 1)

#tab_model(m, show.stat=T, show.r2 = T, show.se = T, pred.labels = c("Intercept",
"AW","Novel", "Desirability", "AW*Novel"), string.pred = c("Fixed Effects"), string.stat
= "t", digits = 3, emph.p = F)
mp <- model_parameters(m)
print_md(mp)
```

Fixed Effects

Parameter	Coefficient	SE	95% CI	t(17071)	p
(Intercept)	-9.84e-03	0.05	(-0.10, 0.09)	-0.20	0.839
SE	0.12	0.02	(0.08, 0.16)	5.69	< .001
novel	0.02	0.01	(-7.68e-03, 0.05)	1.43	0.153
SE × novel	-0.03	0.01	(-0.05, 1.48e-03)	-1.85	0.064

Random Effects

Parameter	Coefficient
SD (Intercept: trait)	0.25
SD (Intercept: subID)	0.46
SD (scale(SE): subID)	0.08
SD (novel: subID)	0.05
Cor (Intercept~scale(SE): subID)	0.21
Cor (Intercept~novel: subID)	0.11
Cor (scale(SE)~novel: subID)	0.76
SD (Residual)	0.84

```
data.frame(r2beta(m))

           Effect          F v1    v2        ncp          Rsq     upper.CL
1           Model  83.218798  3 17082 249.656393 0.0144046470 0.0182696115
2       scale(SE) 178.457415  1 17082 178.457415 0.0103390896 0.0135634919
4 scale(SE):novel   2.873907  1 17082   2.873907 0.0001682135 0.0007817244
3           novel   1.974643  1 17082   1.974643 0.0001155845 0.0006626613
      lower.CL
1 1.118849e-02
2 7.544355e-03
4 1.006827e-06
3 4.131015e-07
```

Simple Effects Other-Self:

```
m<-lmer( scale(eval) ~ scale(SE) * novel + scale(desirability) + ( scale(SE) + novel |
subID) + (1 | trait), OSdf)
#tab_model(m, show.stat=T, show.r2 = T, show.se = T, pred.labels = c("Intercept",
"AW","Novel", "Desirability", "AW*Novel"), string.pred = c("Fixed Effects"), string.stat
= "t", digits = 3, emph.p = F)
mp <- model_parameters(m)
print_md(mp)
```

Fixed Effects

Parameter	Coefficient	SE	95% CI	t(19348)	p
(Intercept)	-6.19e-04	0.05	(-0.10, 0.10)	-0.01	0.990
SE	0.11	0.02	(0.07, 0.15)	5.03	< .001
novel	9.91e-03	0.01	(-0.02, 0.04)	0.70	0.487
desirability	0.11	0.02	(0.06, 0.15)	4.40	< .001

Parameter	Coefficient	SE	95% CI	t(19348)	p
SE × novel	9.05e-03	0.01	(-0.01, 0.03)	0.76	0.444

 # Random Effects

Parameter	Coefficient
SD (Intercept: trait)	0.27
SD (Intercept: subID)	0.50
SD (scale(SE): subID)	0.09
SD (novel: subID)	0.08
Cor (Intercept~scale(SE): subID)	0.20
Cor (Intercept~novel: subID)	-0.05
Cor (scale(SE)~novel: subID)	0.33
SD (Residual)	0.81

```
data.frame(r2beta(m))
```

```
               Effect           F v1    v2         ncp          Rsq
1               Model 201.4088294  4 19360 805.6353174 3.995090e-02
4 scale(desirability) 217.0095888  1 19360 217.0095888 1.108492e-02
2           scale(SE) 134.2706920  1 19360 134.2706920 6.887700e-03
3               novel   0.5666703  1 19360   0.5666703 2.926930e-05
5     scale(SE):novel   0.4735090  1 19360   0.4735090 2.445751e-05
     upper.CL     lower.CL
1 0.0456134189 3.490456e-02
4 0.0141983360 8.349359e-03
2 0.0093976719 4.762702e-03
3 0.0003812832 8.939559e-08
5 0.0003640884 8.144572e-08
```

Zero-Order Effect

```
m<-lmer( scale(eval) ~ scale(SE) * novel + ( scale(SE) + novel | subID) + (1 | trait),
OSdf)
#tab_model(m, show.stat=T, show.r2 = T, show.se = T, pred.labels = c("Intercept",
"AW","Novel", "Desirability", "AW*Novel"), string.pred = c("Fixed Effects"), string.stat
= "t", digits = 3, emph.p = F)
mp <- model_parameters(m)
print_md(mp)
```

 # Fixed Effects

Parameter	Coefficient	SE	95% CI	t(19349)	p
(Intercept)	-3.37e-03	0.05	(-0.11, 0.10)	-0.06	0.949
SE	0.14	0.02	(0.10, 0.18)	6.42	< .001
novel	0.02	0.01	(-0.01, 0.04)	1.10	0.272
SE × novel	8.71e-03	0.01	(-0.01, 0.03)	0.74	0.462

 # Random Effects

Parameter	Coefficient
SD (Intercept: trait)	0.28
SD (Intercept: subID)	0.50
SD (scale(SE): subID)	0.09
SD (novel: subID)	0.08
Cor (Intercept~scale(SE): subID)	0.20
Cor (Intercept~novel: subID)	-0.05
Cor (scale(SE)~novel: subID)	0.34
SD (Residual)	0.81

```
data.frame(r2beta(m))

           Effect           F v1    v2         ncp          Rsq     upper.CL
1           Model 155.0188659  3 19360 465.0565978 2.345802e-02 0.0279268719
2       scale(SE) 234.1847962  1 19360 234.1847962 1.195175e-02 0.0151733076
3           novel   1.4050509  1 19360   1.4050509 7.256968e-05 0.0005108764
4 scale(SE):novel   0.4355612  1 19360   0.4355612 2.249749e-05 0.0003568342
      lower.CL
1 1.954319e-02
2 9.106586e-03
3 2.065748e-07
4 7.841364e-08
```

Study 4

Figure 12. Table of results for only the “competence” study designs in study 4

	Competence Studies		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.97	-1.37 – -0.57	**<0.001**
Age	0.01	0.00 – 0.02	**0.002**
Active	1.13	0.90 – 1.36	**<0.001**
Intermediate	0.46	0.24 – 0.68	**<0.001**
Age*Active	-0.01	-0.01 – 0.00	0.068
Age*Intermediate	-0.00	-0.01 – 0.00	0.636
Random Effects			
σ^2	0.78		
$\tau_{00\ Study}$	0.20		
$\tau_{11\ Study.Age}$	0.00		
$\rho_{01\ Study}$	0.32		
ICC	0.29		
N_{Study}	6		
Observations	4450		
Marginal R^2 / Conditional R^2	0.106 / 0.366		

Figure 13. Graph of results for only the “competence” study designs in study 4

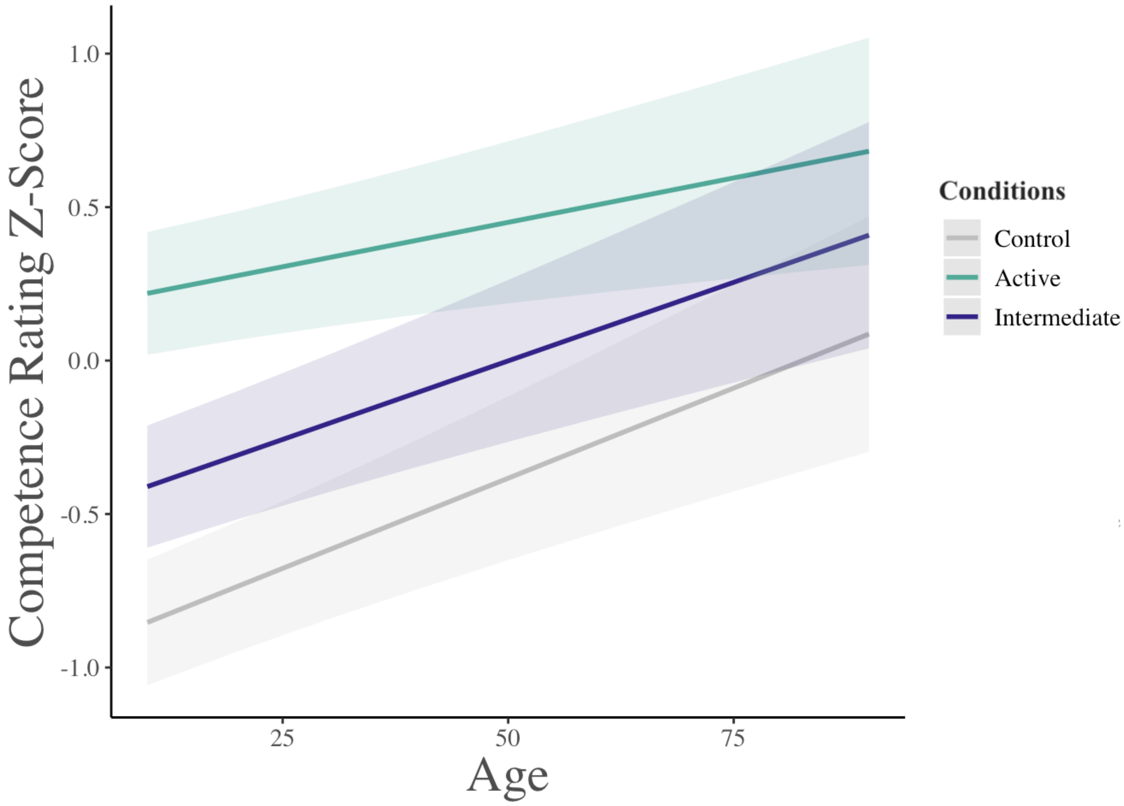


Figure 14. Table of results for only the “similarity” study designs in study 4

	Similarity Studies		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.43	-0.85 – -0.00	**0.048**
Age	0.00	-0.01 – 0.01	0.366
Active	0.46	0.05 – 0.87	**0.029**
Intermediate	0.41	-0.03 – 0.85	0.068
Age*Active	-0.00	-0.01 – 0.01	0.440
Age*Intermediate	-0.00	-0.01 – 0.01	0.663
Random Effects			
σ^2	0.98		
$\tau_{00\ \mathrm{Study}}$	0.09		
$\tau_{11\ \mathrm{Study.Age}}$	0.00		
$\rho_{01\ \mathrm{Study}}$	-0.63		
ICC	0.06		
N_{Study}	11		
Observations	5078		
Marginal R^2 / Conditional R^2	0.006 / 0.061		

Figure 15. Graph of results for only the “similarity” study designs in study 4

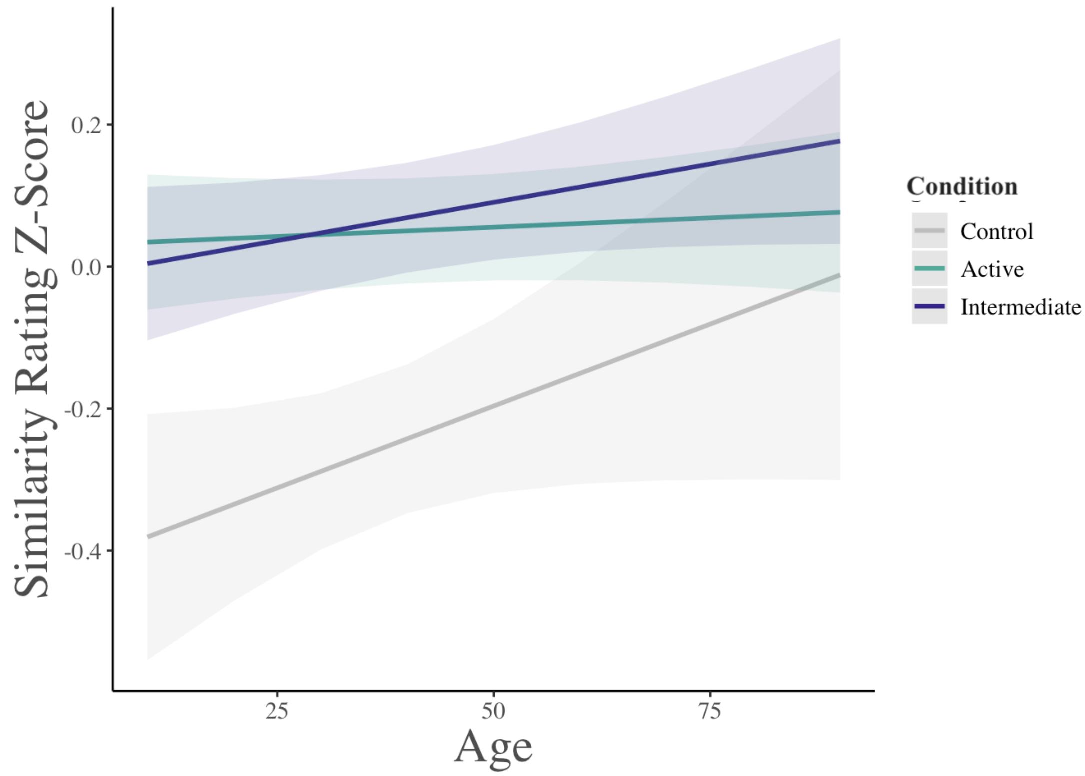


Figure 16. Demographic breakdown of Studies in Study 1 and 5 metanalysis

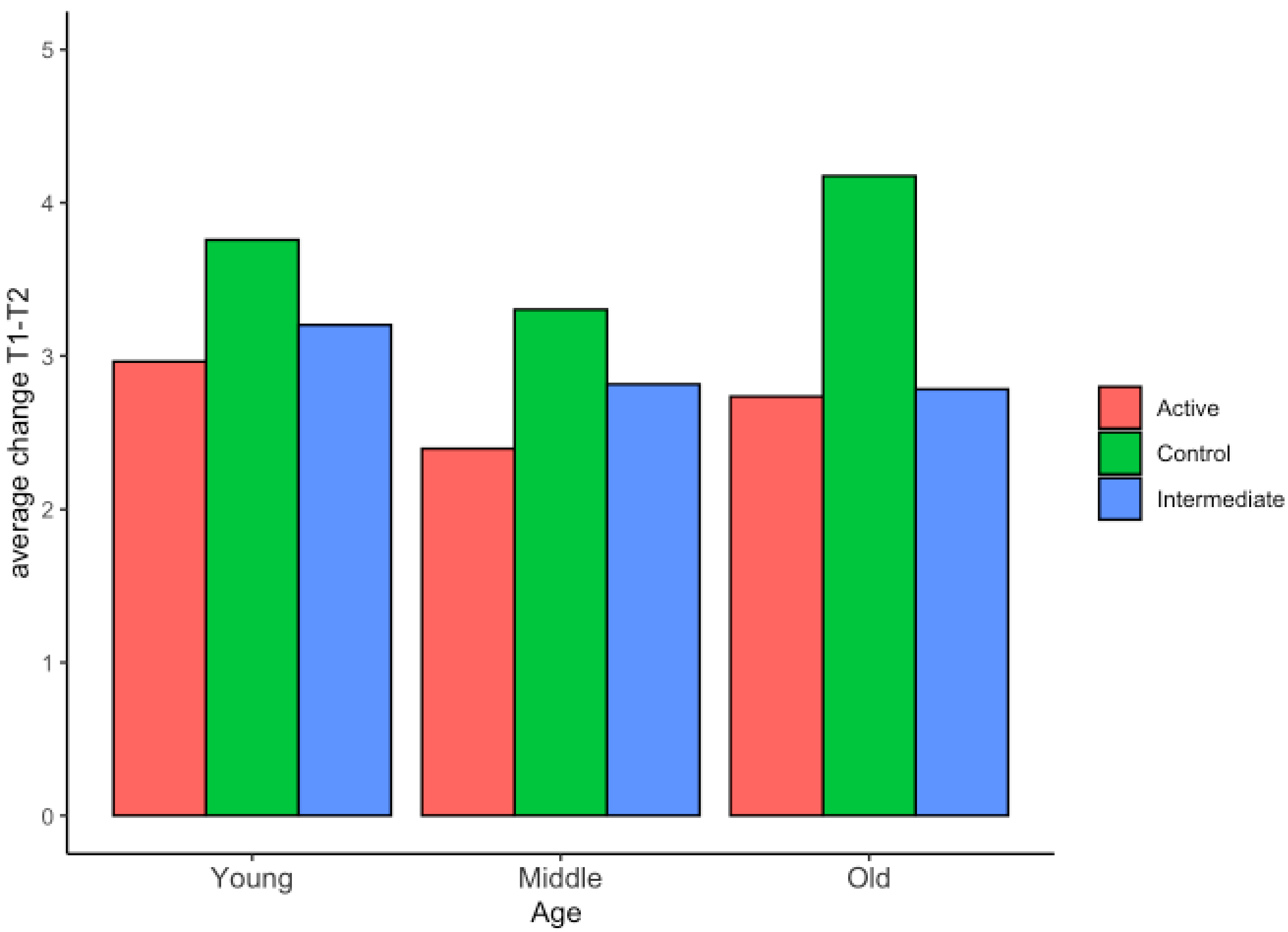
Study	Sample	Race	Gender	Age
Antonym (Study 1 + 6)	*N* = 392	Asian - 2.5% Black - 3.5% Mixed Race - 1% Other - 3.0% White - 89.9%	Female - 68.2% Male - 31.8%	SD_{Age} – 11.14 M_{Age} – 35.38
Delay RW (Study 1 + 6)	*N* = 927	American Indian or Alaska Native - 0.1% Mixed Race - 2% Asian - 7.2% Black or African American - 3.9% Other - 3.8% Prefer not to answer - 0.8% White - 82.3%	Female - 70.5% Male - 27.9% Other - 1.2% Prefer not to answer - 0.3%	SD_{Age} – 10.91 M_{Age} – 32.95
originalT1 (Study 1 + 6)	*N* = 507	Asian - 4.7% Mixed Race – 0.6% Black or African American - 2.2% Other - 3.2% Prefer not to answer - 0.6% White - 88.8%	Female - 63.3% Male - 35.3% Other - 1.0% Prefer not to answer - 0.4%	SD_{Age} – 13.40 M_{Age} – 36.65

Perspective (Study 1 + 6)	$N = 172$	Asian - 5.5% Mixed Race - 0.5% Black or African American - 3.8% Other - 1.1% White - 89.0%	Female - 67.6% Male - 31.9% Other - 0.5%	SD_{Age} – 11.91 M_{Age} – 36.03
Mech2 (Study 1 + 6)	$N = 750$	American Indian - 0.1% Mixed Race – 1.1% Asian - 8.7% Black or African American - 4.6% Hawaiian/ Pacific Islander - 0.1% Other - 3.8% Prefer not to answer - 1.1% White - 80.3%	Female - 69.6% Male - 28.9% Other - 0.9% Prefer not to answer - 0.5%	SD_{Age} = 12.35 M_{Age} = 33.58
Mech3 (Study 1 + 6)	$N = 744$	American Indian - 1.0% Mixed Race – 4.3% Asian - 8.1% Black or African American - 9.3% Other - 2.5% Prefer not to answer - 0.4% White - 74.2%	Female - 52.6% Male - 45.3% Other - 2.0% Prefer not to answer - 0.1%	SD_{Age} – 10.93 M_{Age} – 32.46
Vividness (study 4)	$N = 182$	African American – 6.0% Mixed Race – 4.32% Asian – 6.0% Hispanic – 2.16% Native American – 0.12% Other – 1.80% Pacific Islander – 0.12% White/Caucasian – 79.47%	Female – 60.38% Male – 37.94% Other – 1.2% Prefer not to answer – 0.48%	SD_{Age} – 24.53 M_{Age} – 36.96
Womensim (Study 1 + 6)	$N = 427$	Mixed Race – 2.40% Asian – 11.79% Black or African American – 3.30% Other – 2.83% Prefer not to answer – 1.42% White – 78.3%	Female – 100%	SD_{Age} - 11.37 M_{Age} – 31.29
Study1 (Study 1 + 6)	$N = 139$	Data unavailable	Female – 62.7%	SD_{Age} – 12.45 M_{Age} – 41.35
Study2a (Study 1 + 6)	$N = 334$	Data unavailable	Female – 68.89%	SD_{Age} – 12.94 M_{Age} – 36.97
Study2b (Study 1 + 6)	$N = 186$	Data unavailable	Female – 52.23%	SD_{Age} – 12.55 M_{Age} – 36.19
Study4a (study 4)	$N = 266$	Data unavailable	Female – 25.48%	SD_{Age} = 11.58 M_{Age} = 36.67
Study4b (Study 1 + 6)	$N = 321$	Data unavailable	Female – 51.40%	SD_{Age} = 11.60 M_{Age} = 36.67
Study6 (Study 1 + 6)	$N = 687$	Data unavailable	Female – 49.88%	SD_{Age} = 12.19 M_{Age} = 38.47

Thesis2 (Study 1 + 6)	*N* = 724	Data unavailable	Data unavailable	SD_{Age} – 11.92 M_{Age} – 38.85
Thesis3 (Study 1 + 6)	*N* = 683	Data unavailable	Data unavailable	SD_{Age} – 11.59 M_{Age} – 36.46
Repetition (Study 1 + 6)	*N* = 205	Asian – 5.85%x Black or African American – 1.46% Other – 3.41% Prefer not to respond – 1.46% White – 87.80%	Female 84.88% Male – 14.15% Other – 0.49% Prefer not to respond – 0.49%	SD_{Age} – 11.13 M_{Age} – 36.54

Figure 17. Change in self-ratings pretest to post test for similarity studies in study 4 - mean(abs(selft1 - selfT2))

```
##           cond    Bin    N   change       sd         se         ci
## 1       Active Middle 2671 2.393518 2.444951 0.04730786 0.09276375
## 2       Active    Old  674 2.734190 3.001866 0.11562756 0.22703414
## 3       Active  Young 3323 2.963042 3.195042 0.05542572 0.10867202
## 4      Control Middle  128 3.302455 3.058248 0.27031352 0.53490168
## 5      Control    Old   40 4.175000 3.359848 0.53123863 1.07453155
## 6      Control  Young  232 3.757697 3.925334 0.25771081 0.50776416
## 7 Intermediate Middle 1065 2.813989 2.645684 0.08107055 0.15907631
## 8 Intermediate    Old  278 2.781883 2.661802 0.15964427 0.31427013
## 9 Intermediate  Young 1341 3.201756 3.183141 0.08692436 0.17052264
```



ANCOVA

ANCOVA - change

	Sum of Squares	df	Mean Square	F	p	η²p
Condition	290.7	2	145.33	16.83	<.001	0.003
Age	140.3	2	70.15	8.13	<.001	0.002
Condition*Age	43.3	4	10.82	1.25	0.286	0.001
Residuals	84112.2	9743	8.63			

Post Hoc Tests

Post Hoc Comparisons - Bin ✻ cond

Comparison									
Bin	cond		Bin	cond	Mean Difference	SE	df	t	p_{tukey}
Middle	Active	-	Middle	Control	-0.9089	0.2659	9743	-3.419	0.018
		-	Middle	Intermediate	-0.4205	0.1065	9743	-3.949	0.003
		-	Old	Active	-0.3407	0.1267	9743	-2.690	0.151
		-	Old	Control	-1.7815	0.4680	9743	-3.806	0.004
		-	Old	Intermediate	-0.3884	0.1852	9743	-2.097	0.475
		-	Young	Active	-0.5695	0.0764	9743	-7.459	<.001
		-	Young	Control	-1.3642	0.2011	9743	-6.783	<.001
		-	Young	Intermediate	-0.8082	0.0983	9743	-8.219	<.001
	Control	-	Middle	Intermediate	0.4885	0.2749	9743	1.777	0.698
		-	Old	Active	0.5683	0.2833	9743	2.006	0.539
		-	Old	Control	-0.8725	0.5322	9743	-1.639	0.783
		-	Old	Intermediate	0.5206	0.3138	9743	1.659	0.772
		-	Young	Active	0.3394	0.2647	9743	1.282	0.937
		-	Young	Control	-0.4552	0.3235	9743	-1.407	0.895
		-	Young	Intermediate	0.1007	0.2718	9743	0.370	1.000
	Intermediate	-	Old	Active	0.0798	0.1446	9743	0.552	1.000
		-	Old	Control	-1.3610	0.4732	9743	-2.876	0.095
		-	Old	Intermediate	0.0321	0.1979	9743	0.162	1.000
		-	Young	Active	-0.1491	0.1035	9743	-1.441	0.882
		-	Young	Control	-0.9437	0.2129	9743	-4.433	<.001
		-	Young	Intermediate	-0.3878	0.1206	9743	-3.215	0.035
Old	Active	-	Old	Control	-1.4408	0.4782	9743	-3.013	0.065
		-	Old	Intermediate	-0.0477	0.2094	9743	-0.228	1.000
		-	Young	Active	-0.2289	0.1241	9743	-1.844	0.653
		-	Young	Control	-1.0235	0.2237	9743	-4.576	<.001
		-	Young	Intermediate	-0.4676	0.1387	9743	-3.370	0.022
	Control	-	Old	Intermediate	1.3931	0.4969	9743	2.804	0.114
		-	Young	Active	1.2120	0.4674	9743	2.593	0.189
		-	Young	Control	0.4173	0.5030	9743	0.830	0.996
		-	Young	Intermediate	0.9732	0.4714	9743	2.064	0.498
	Intermediate	-	Young	Active	-0.1812	0.1834	9743	-0.988	0.987
		-	Young	Control	-0.9758	0.2613	9743	-3.735	0.006
		-	Young	Intermediate	-0.4199	0.1936	9743	-2.168	0.427
Young	Active	-	Young	Control	-0.7947	0.1995	9743	-3.983	0.002
		-	Young	Intermediate	-0.2387	0.0951	9743	-2.511	0.226
	Control	-	Young	Intermediate	0.5559	0.2089	9743	2.661	0.162

Note. Comparisons are based on estimated marginal means

Study 5 - The effect of Semantic vs. Episodic self-knowledge activation on SIM

Study 2 found that the Other-then-self condition led to greater self-concept change than the Self-then-other condition when simulating similar targets. Study 5 aimed to further investigate the impact of self-knowledge activation by replicating this finding and extending the paradigm to examine simulation across two domains of self-knowledge. In Study 2, all participants simulated a target by rating them on traits related to competence. Here, participants either rated a target on traits related to competence (a semantic form of simulation) or wrote about them in three situations that evoke competence (an episodic form of simulation). We expected to replicate the main effect of Study 2, where the Other-then-self condition showed greater SIM than Self-then-other condition. We also predicted that the Other-then-self condition paired with Semantic simulation would yield the strongest effects across all conditions. These hypotheses, analysis plans, and all materials for this study were pre-registered on the Open Science Framework at: https://osf.io/6xa3q/?view_only=ff8815d8b3294434beedbe7fff1f5caf

Participants

Participants (N = 780) were recruited from Prolific Academic. This sample size provided 95% power at an $\alpha = 0.05$ to detect the effect of self-knowledge activation (Other-then-self vs. Self-then-other) on both simulation types (Semantic vs. Episodic), based on results from a pilot study (see Supplement). Participants were excluded prior to analyses based on three a priori criteria: if they provided too few unique answers ($N = 0$), if they completed the study in an unreasonably short period of time ($N = 2$), or if they reported poor English proficiency ($N = 11$). The final sample size following these exclusions was N = 767 (28.9% male, 69.6% female, 0.7% non-binary, agender, or genderqueer, 0.3% other, 0.5% prefer not to answer; $M_{age} = 33.58$, $SD_{age} = 12.34$; 80.3% White, 4.6% Black or African American, 8.7% Asian, 1.1% Mixed Race, 4.1% other, 1.2% prefer not to respond).

Procedure

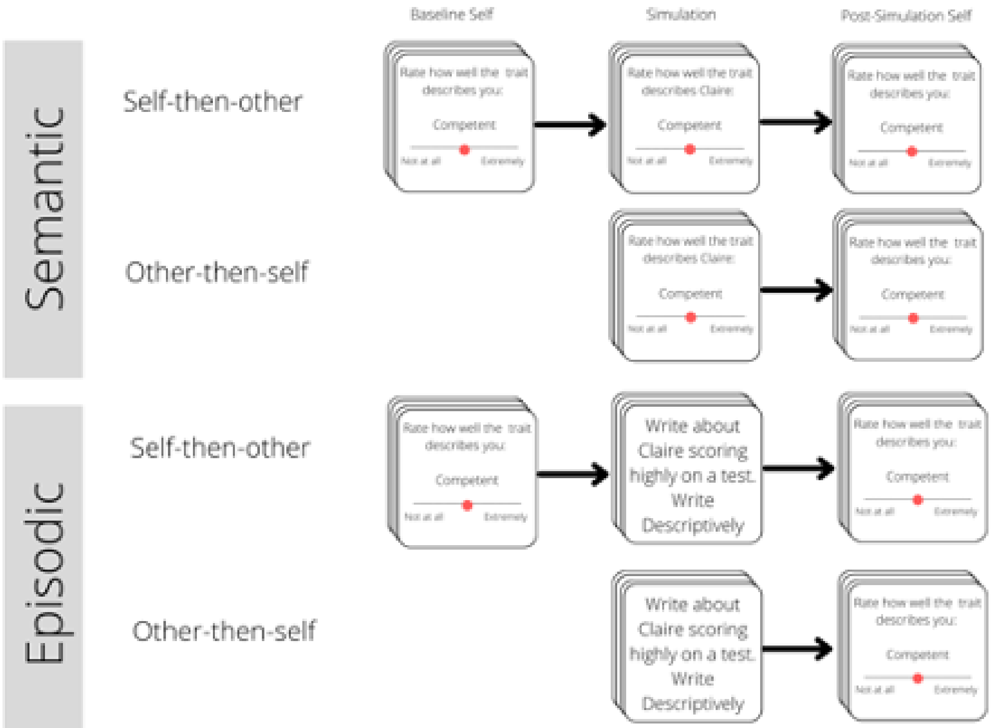
There were up to three blocks to this experiment, closely paralleling Study 2 (Figure 5). All participants in the Self-then-other condition first completed the baseline self-ratings. Half of these participants were assigned to the Semantic condition, where they rated how well a series of eight adjectives applied to them on a sliding scale from "not at all" to "extremely," with the slider at a starting point in the middle. As in Study 2, the words were selected from a list of traits that reflect the trait 'competence.' Participants in the Other-then-self condition did not complete the baseline self-ratings.

In the simulation block of the study, all participants provided the name of an individual who was someone they deemed similar to them and highly competent, based on a definition of competence provided in the survey. Participants in the Semantic conditions rated the target they provided on a series of competence traits, in an identical manner to Study 2. Participants in the episodic conditions simulated this target in a series of three situations, which had been pre-rated to evoke competence. Participants wrote about the experience in detail, focusing in particular on how the target would feel. They were required to write at least 150 characters for each situation.

In the final post-simulation self block of the study, all participants again rated how well the eight competence adjectives applied to them. Our primary dependent variable was participant self-ratings of competence in this post-simulation block. By examining the post-simulation ratings of competence, we could determine the extent to which the Other-then-self vs. Self-then-other conditions impacted SIM.

Figure 5.

Study 5 Design



Note. Task Schematic for Study 5. Half of the participants completed a Semantic condition and half completed an episodic condition. For both conditions, half of the participants rated how well a series of eight traits related to competence applied to them (Self-then-other conditions). All participants then completed a simulation block, in which they either rated a similar target on eight competent traits (Semantic) or wrote about them in three competent scenarios (Episodic) before rating themselves on the same eight traits.

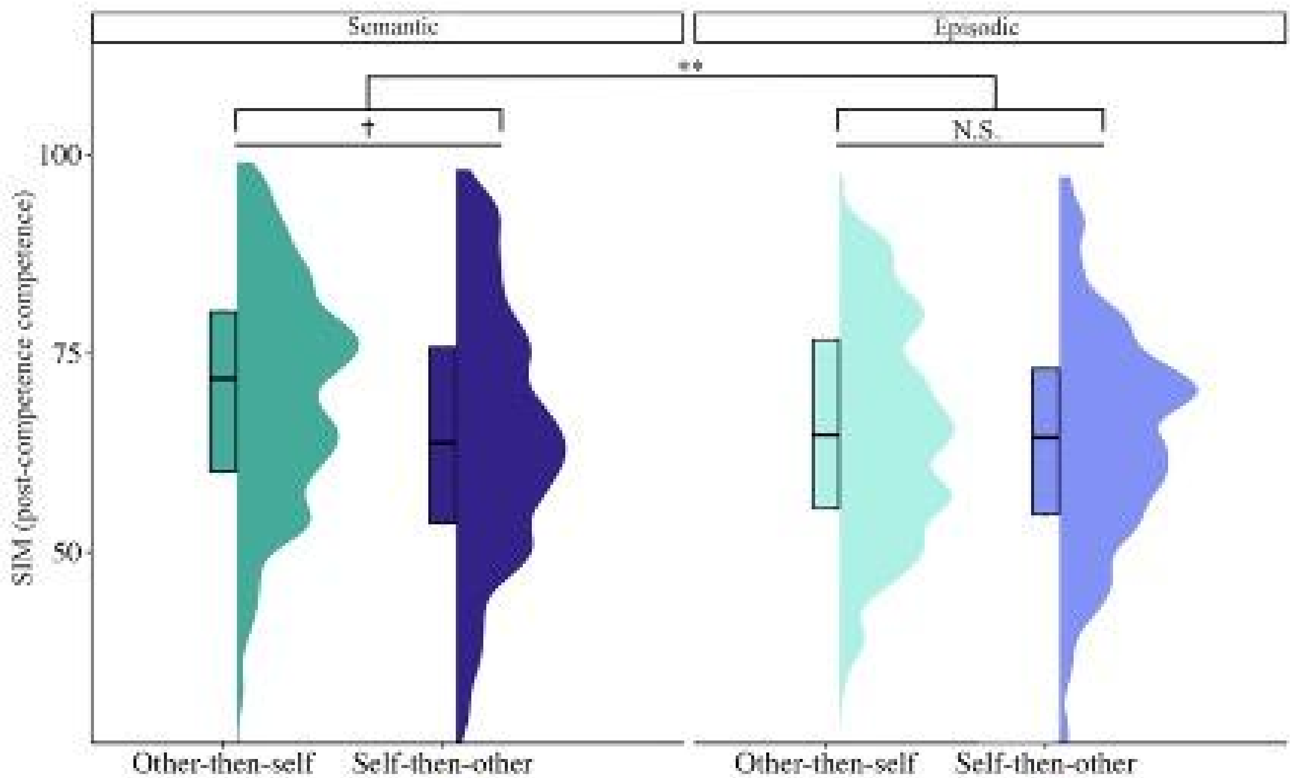
Results

We tested our first hypothesis, that the Other-then-self condition would lead to greater SIM effects than the Self-then-other condition, with a 2 (Self-then-other vs. Other-then-self) x 2 (Episodic vs. Semantic) ANOVA (Figure 6). As expected, this analysis revealed a main effect of condition, such that those in the Other-then-self condition reported higher competence ratings (M = 67.5, SD = 14.6) than those in the Self-then-other condition (M = 64.1, SD = 15.9; ($F(1,752) = 9.67$, $p = 0.002$, $\eta^2_p = 0.013$). These results suggest that the Other-then-self condition strengthens SIM effects across both Semantic and Episodic forms of simulation.

We tested our second hypothesis, that the Other-then-self condition would elicit greater effects for Semantic simulation than Episodic simulation, by examining the interaction effect from the above 2 (Self-then-other vs. Other-then-self) x 2 (Episodic vs. Semantic) ANOVA. The interaction between condition and simulation type was marginally significant ($F(1,752) = 3.65$, $p = 0.057$, $\eta^2_p = 0.005$). In a follow-up analysis of simple effects, we found that the effect of the Other-then-self condition was significant in the Semantic condition (*t(379.8)* = 3.43, p < 0.001, d = 0.35), and not significant in the Episodic condition (*t(377.18)* = 0.88, p = 0.38, d = 0.09). These results suggest that Semantic simulation may influence semantic self-knowledge more than Episodic simulation, though the difference between the two conditions is not robust.

Figure 6.

Impact of Order on Semantic and Episodic Knowledge



Note. Study 5 found a significant main effect of self-knowledge activation such that participants in the Other-then-self condition reported higher competence scores than those in the Self-then-other condition.

Discussion

Study 5 replicated the findings from Study 2, providing further evidence that the Other-then-self condition leads to greater SIM effects than the Self-then-other condition when simulating similar others. This effect was directionally similar across simulation types (though only significant in the Semantic condition), further validating the robustness of this effect. We suspect that the effects were stronger for semantic simulation because the self-ratings were all on semantic knowledge; had the episodic simulation condition likewise measured the effects of simulation on episodic self-knowledge, we would expect that any differences between semantic and episodic simulation might disappear.

Alternatively, these results may speak to the nature of semantic knowledge vs. episodic memories. Semantic knowledge is thought to be superordinate to episodic memories (Tulving, 1985), more by motivation and state (Squire et al., 1976), and thus may be more elastic than episodic knowledge. That is, it should be influenced more by momentary shifts in self-knowledge than episodic memories, stretching and shifting with new contexts, but later returning to its stable shape. Further research could investigate additional forms of simulation (i.e., rating memories) to make stronger claims about the generalizability of this result, and differences across self-knowledge types.

Study 6 - Similar vs. Dissimilar Targets

In Study 5, we replicated the finding that considering a similar target before, rather than after activating self-knowledge yields greater SIM effects. However, other-then-self self-knowledge activation may *not* likewise increase SIM for dissimilar others, as simulating dissimilar targets spontaneously activates less self-knowledge than simulating similar targets (Ames, 2004a, 2004b; Kunda & Spencer, 2003). Indeed, Study 1 replicated prior work showing that simulating dissimilar targets resulted in weaker SIM effects (Meyer et al., 2019). For dissimilar targets, the Self-then-other condition may be a necessary route by which simulators can activate self-knowledge and make it labile. For example, reading an article about Mark Zuckerberg's fame and fortune may not prompt someone to think about their own career path, unless explicit comparisons are made. Perhaps if the article quoted Zuckerberg saying, "my career path started out the same way most people's do," this would prompt the reader to consider their own path first. For dissimilar targets, the Self-then-other condition may elicit self-other comparisons that reveal similarities (Todd et al., 2016). In contrast, for similar targets, the Self-then-other condition may be more likely to reveal self-other differences.

In Study 6, we tested this possibility by having participants simulate either a similar or dissimilar target, either before (Other-then-self) or after (Self-then-other) considering the self. We expected three outcomes: first, we expected to replicate findings from Study 1 that simulating a similar target would yield a stronger SIM effect than simulating a dissimilar target. Second, we expected to replicate the results from Studies 2 and 5 for similar targets, such that the SIM effect would be greatest for the Other-then-self condition. Finally, we expected the reverse to be true for dissimilar targets, such that the SIM effect would be strongest for the Self-then-other condition. However, if SIM is only impacted by order of activation (Other-then-self vs. Self-then-other), we would expect to see an identical effect across targets. These hypotheses and all materials for this study were pre-registered on the Open Science Framework at:

https://osf.io/egm7s/?view_only=2a0f94b2553b4a22aaa41e6c38cce829

Participants

Participants (N = 780) were recruited from Prolific Academic. This sample size provided 95% power at an $\alpha = 0.05$ to detect the effect of activation of self-knowledge (Other-then-self vs. Self-then-other) on both target types (Similar vs. Dissimilar), based on results from a pilot study (see Supplement). Participants were excluded prior to analyses based on 3 a priori criteria: if they provided too few unique answers (n = 0), if they completed the study in an unreasonably short period of time (n = 17), and if they reported poor English proficiency (n = 2). The final sample size following these exclusions was 761 (45.3% male, 52.6% female, 2.0% nonbinary/agender, 0.1% prefer not to answer; M_{age} = 32.5 years, SD_{age} = 10.9 years, 74.1% white, 9.3% Black, 8.1% Asian, 1.1% American Indian or Alaska Native, 4.5% Mixed Race, 2.5% other, 0.4% prefer not to answer).

Procedure

The procedure was similar to Study 5, with identical Self-then-other and Other-then-self conditions. Targets were either Similar or Dissimilar. Participants in the Similar condition were asked to generate a similar target, who they then rated on a series of competence traits; participants in the Dissimilar condition rated the same traits for Mark Zuckerberg, chosen for being rated highly on competence but likely dissimilar to most people (Thornton & Mitchell, 2018). In the post-simulation self block of the study, all participants again rated how well the eight competence adjectives applied to them or Mark Zuckerberg. Our primary dependent variable was participant self-ratings of competence in this post-simulation block. By examining the post-simulation ratings, we could determine the extent to which Other-then-self vs. Self-then-other conditions impacted SIM across targets.

Results

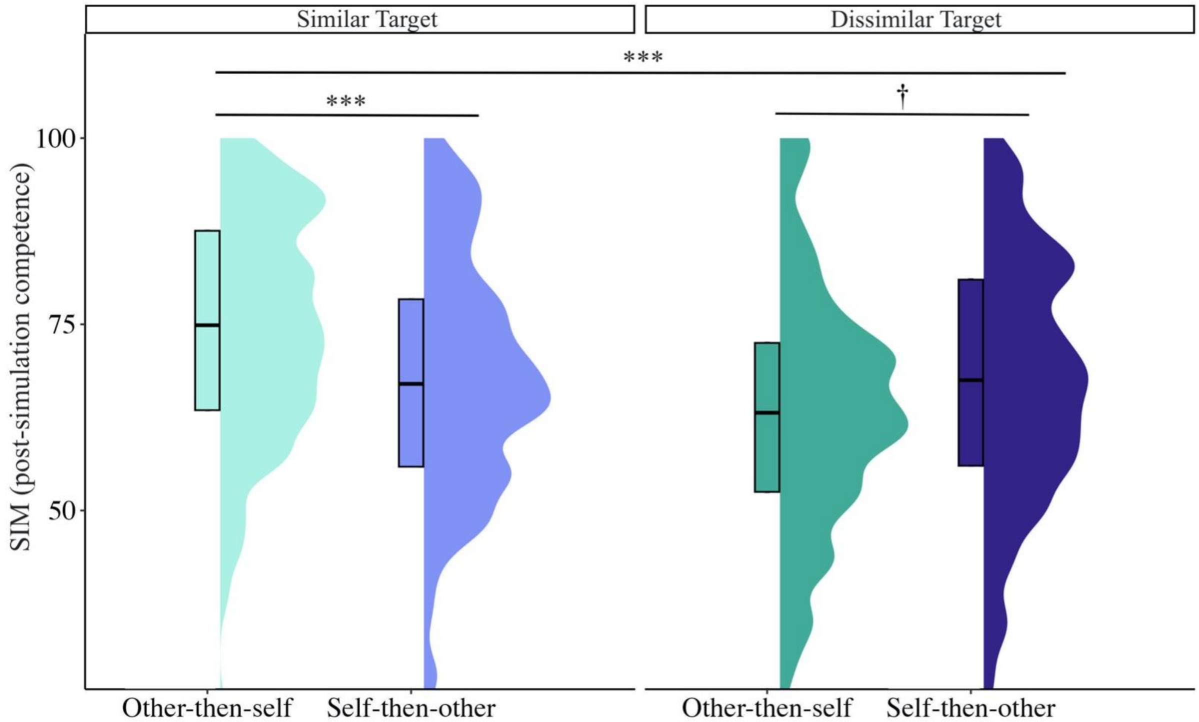
Our first hypothesis was that SIM effects would be greater for Similar than Dissimilar targets. To test this, we conducted an independent samples t-test comparing post-simulation competence ratings for participants who simulated a similar target to those who simulated a dissimilar target (Figure 7). Results showed a main effect of target ($t(759) = 4.73$, $p < 0.001$, $d = 0.34$), such that those who simulated a similar target rated themselves more highly on competence (M = 70.7, SD = 16.6) than those who simulated a dissimilar target (M = 64.9, SD = 17.5).

Our second hypothesis was that we would replicate the effect of self-knowledge activation order from Studies 2 and 3. To test this, we conducted a t-test comparing the Other-then-self and Self-then-other conditions for those who simulated a similar target. As expected, we found that participants in the Similar + Other-then-self condition had significantly higher competence ratings (M = 74.1, SD = 16) than those in the Similar + Self-then-other condition (M = 67.5, SD = 16.5; $t(757) = 3.8$, $p < 0.001$, $d = -0.40$).

Our third hypothesis was that the Other-then-self condition would enhance SIM effects for similar but not dissimilar targets, evidenced by an interaction between target and order. To test this, we conducted a 2 (order – Other-then-self vs. Self-then-other) x 2 (target – Similar vs. Dissimilar) ANOVA. This ANOVA revealed an interaction between target and order ($F(1,760) = 20.5$, $p < 0.001$, $\eta 2p = 0.03$), in line with our hypothesis. The effect observed in Study 1 and Study 2 was reversed for the Dissimilar condition, such that those in the Dissimilar + Other-then-self condition had lower scores (M = 62.6, SD = 17.5) than those in the dissimilar target + Self-then-other condition (M = 67.1, SD = 17.1; $t(757) = 2.6$, $p = 0.05$, $d = 0.26$).

Figure 7.

Impact of Order on Similar vs. Dissimilar Targets



Note. Study 4 found a significant main effect of target, such that simulating similar targets led to higher self-ratings of competence post-simulation. For similar targets, the Other-then-self condition elicited higher competence scores than the Self-then-other condition. In contrast, the Other-then-self condition dampened effects for dissimilar targets.

Discussion

Results from Study 6 demonstrated that the Other-then-self condition strengthened SIM effects for similar, but not dissimilar, targets when compared to the Self-then-other condition. This replicates findings from studies 2 and 3, that the Other-then-self condition was most effective at altering self-concept when simulating a similar target that spontaneously activates high amounts of self-knowledge. In contrast, competence ratings were lowest in the dissimilar target + Other-then-self condition. This suggests that simulating dissimilar targets does not spontaneously activate enough self-knowledge to alter self-concept as effectively as simulating similar targets does. Dissimilar targets *can* change self-knowledge if that self-knowledge is explicitly activated prior to simulating the target. That is, the Self-then-other condition was most useful in scenarios where low amounts of self-knowledge were spontaneously activated during simulation.