Mediation results

****

Model = 4
Y = Gossip
X = Age
M = Mate_Val

remember df for t = df2

Sample size
81

****

Outcome: Mate_Val M

X→M path a

Model Summary

R	R-sq	F	df1	df2	p
.3815	.1455	13.4522	1.0000	79.0000	.0004

Model

		coeff	se	t	p	
	constant	3.7981	.2366	16.0558	.0000	
X	Age	-.0266	.0073	-3.6677	.0004	want p<.05

****

Outcome: Gossip Y

M→Y path b,
X→Y path c'

Model Summary

R	R-sq	F	df1	df2	p
.4614	.2129	10.5468	2.0000	78.0000	.0001

Model

		coeff	se	t	p	
	constant	1.1963	.5495	2.1771	.0325	
M	Mate_Val	.4546	.1266	3.5921	.0006	want p<.05
X	Age	-.0113	.0088	-1.2753	.2060	usualy want p>.05 but see below

************************** TOTAL EFFECT MODEL ****************************

Outcome: Gossip Y

Model Summary

R	R-sq	F	df1	df2	p
.2875	.0827	7.1180	1.0000	79.0000	.0093

X→Y path c

Model

		coeff	se	t	p	
	constant	2.9230	.2855	10.2397	.0000	
X	Age	-.0234	.0088	-2.6680	.0093	want p<.05

coeff values are unstd. b.

***************** TOTAL, DIRECT, AND INDIRECT EFFECTS ********************

Total effect of X on Y

Effect	SE	t	p
-.0234	.0088	-2.6680	.0093

c path

repeated info

Direct effect of X on Y

Effect	SE	t	p
-.0113	.0088	-1.2753	.2060

c' path

Indirect effect of X on Y

	Effect	Boot SE	BootLLCI	BootULCI
Mate_Val	-.0121	.0056	-.0276	-.0037

mediation effect.

want CI to NOT include zero to show mediation even if c' $p<.05$

various effect sizes

Partially standardized indirect effect of X on Y

	Effect	Boot SE	BootLLCI	BootULCI
Mate_Val	-.0122	.0052	-.0254	-.0040

Completely standardized indirect effect of X on Y

	Effect	Boot SE	BootLLCI	BootULCI
Mate_Val	-.1489	.0632	-.3044	-.0480

Ratio of indirect to total effect of X on Y

	Effect	Boot SE	BootLLCI	BootULCI
Mate_Val	.5179	.9902	.1568	1.6690

Ratio of indirect to direct effect of X on Y

	Effect	Boot SE	BootLLCI	BootULCI
Mate_Val	1.0744	31.7645	-1.9585	32.7968

R-squared mediation effect size (R-sq_med)

	Effect	Boot SE	BootLLCI	BootULCI
Mate_Val	.0662	.0388	.0122	.1759

Preacher and Kelley (2011) Kappa-squared

	Effect	Boot SE	BootLLCI	BootULCI
Mate_Val	.1458	.0599	.0464	.2843

recommend effect size K^2 (interpret as R^2)

Normal theory tests for indirect effect

Effect	se	Z	p
-.0121	.0048	-2.5190	.0118

Sobel test

want $p<.05$

w/ process you won't have pr2

Results

Treatment condition for housing (either treated or control group) was used to predict days in housing, with housing contacts expected to mediate the relationship between treatment condition and days in housing. Data were screened for multivariate outliers, leverage and influence and two cases were removed as outliers and influential data points. All other assumptions of regression were checked and appeared satisfactory.

See Figure 1 for visual diagram of the mediated relationship. First, using steps described
and Hayes (2013) process plugin for SPSS
by Baron and Kenny (1986), treatment was a significant predictor of days in housing (the *c* pathway), as shown in Table 1. The treatment condition showed a higher number of days in housing than the control condition, $t(105) = 2.72, p = .01, pr^2 = .07$. Second, treatment condition was used to predict the mediator variable of housing contacts (the *a* pathway), which showed that treatment condition was positively related to housing contacts, $t(105) = 2.98, p = .01, pr^2 = .08$. Third, the relationship between the mediator housing contacts and days in housing was examined controlling for the treatment condition (the *b* pathway). Number of housing contacts was positively related to the number of days in housing, $t(104) = 4.96, p < .001, pr^2 = .19$. Lastly, the mediated relationship between treatment condition and days in housing was examined for a drop in prediction when the mediator was added to the model (the *c'* pathway). Full mediation was found, showing that the relationship between treatment condition and days in housing was no longer significant after controlling for housing contacts, $t(104) = 1.50, p = .14, pr^2 = .02$. The Sobel test was used to determine that the *ab* effect was significantly greater than zero, $Z = 2.55, p = .01$.

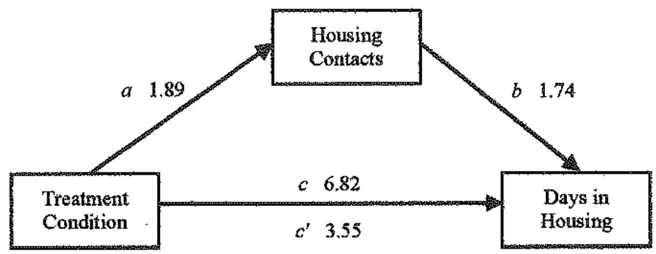

Figure 1. Mediated relationship between treatment condition and days in housing with housing contacts as the mediator.

Table 1

Model Summaries for Mediation Analysis.

Model	F	p	R^2
Treatment Condition predicting Days in Housing	(1, 105) = 7.38	<.01	.07
Treatment Condition predicting Housing Contacts	(1, 105) = 8.87	<.01	.08
Treatment Condition and Housing Contacts predicting Days in Housing	(1, 104) = 16.82	<.001	.24

moderation output

****

Model = 1
Y = Aggressi
X = Vid_Game
M = CaUnTs

Sample size
442

****

Outcome: Aggressi

Model Summary

R	R-sq	F	df1	df2	p
.6142	.3773	90.5311	3.0000	438.0000	.0000

Model

		coeff	se	t	p	LLCI	ULCI
	constant	39.9671	.4750	84.1365	.0000	39.0335	40.9007
main effects	CaUnTs	.7601	.0466	16.3042	.0000	.6685	.8517
	Vid_Game	.1696	.0759	2.2343	.0260	.0204	.3188
interact	int_1	.0271	.0073	3.7051	.0002	.0127	.0414

want $p < .05$

Interactions:

int_1 Vid_Game X CaUnTs

****

Conditional effect of X on Y at values of the moderator(s): want sig

	CaUnTs	Effect	se	t	p	LLCI	ULCI
Low Callous	-9.6177	-.0907	.1058	-.8568	.3920	-.2986	.1173
Avg	.0000	.1696	.0759	2.2343	.0260	.0204	.3188
High	9.6177	.4299	.1010	4.2562	.0000	.2314	.6284

slopes for X → vid game

Values for quantitative moderators are the mean and plus/minus one SD from mean.
Values for dichotomous moderators are the two values of the moderator.

*************** JOHNSON-NEYMAN TECHNIQUE ***********************

Moderator value(s) defining Johnson-Neyman significance region(s):

Value % below % above

-17.1002	1.3575	98.6425
-.7232	48.8688	51.1312

Conditional effect of X on Y at values of the moderator (M)

CaUnTs	Effect	se	t	p	LLCI	ULCI	
-18.5950	-.3336	.1587	-2.1027	.0361	-.6454	-.0218	sig for Low values
-17.1002	-.2931	.1492	-1.9654	.0500	-.5863	.0000	
-16.4450	-.2754	.1451	-1.8987	.0583	-.5605	.0097	
-14.2950	-.2172	.1319	-1.6467	.1003	-.4765	.0420	
-12.1450	-.1590	.1194	-1.3319	.1836	-.3937	.0756	
-9.9950	-.1009	.1077	-.9361	.3497	-.3126	.1109	not sig.
-7.8450	-.0427	.0972	-.4390	.6609	-.2338	.1484	
-5.6950	.0155	.0882	.1757	.8606	-.1579	.1889	
-3.5450	.0737	.0813	.9059	.3655	-.0862	.2336	
-1.3950	.1319	.0771	1.7111	.0878	-.0196	.2833	
-.7232	.1501	.0763	1.9654	.0500	.0000	.3001	
.7550	.1901	.0759	2.5053	.0126	.0410	.3392	
2.9050	.2482	.0779	3.1878	.0015	.0952	.4013	sig for Low + High values
5.0550	.3064	.0829	3.6980	.0002	.1436	.4693	
7.2050	.3646	.0903	4.0360	.0001	.1871	.5422	
9.3550	.4228	.0997	4.2386	.0000	.2267	.6188	
11.5050	.4810	.1106	4.3490	.0000	.2636	.6983	
13.6550	.5392	.1225	4.4013	.0000	.2984	.7799	
15.8050	.5973	.1352	4.4188	.0000	.3317	.8630	
17.9550	.6555	.1484	4.4160	.0000	.3638	.9473	
20.1050	.7137	.1621	4.4017	.0000	.3950	1.0324	
22.2550	.7719	.1762	4.3814	.0000	.4256	1.1181	
24.4050	.8301	.1905	4.3580	.0000	.4557	1.2044	

****

Data for visualizing conditional effect of X of Y:

Vid_Game	CaUnTs	yhat
L -6.9622	L -9.6177	33.2879
A .0000	-9.6177	32.6568
H 6.9622	-9.6177	32.0256
-6.9622	A .0000	38.7861
.0000	.0000	39.9671
6.9622	.0000	41.1481
-6.9622	H 9.6177	44.2844
.0000	9.6177	47.2774
6.9622	9.6177	50.2705

use this data to graph

Results

Attendance and number of books read during a semester were used to predict final class grade. Data were checked for outliers and assumptions of regression, and no violations were found. The PROCESS plug-in for SPSS was used to analyze the interaction between attendance and books read in a semester (Hayes, 2013). The main effects of attendance and books were significant predictors of grades, $F(3,37)=9.06, p=.001, R^2 = .33$. As a person attended more classes, their course grade increased significantly, $\beta = .33$, $t(37) = 2.20, p=.04, pr^2=.11$. Students could also increase their course grades by reading more books throughout the semester, $\beta=.35$, $t(37) = 2.30, p=.03, pr^2=.12$. Course grades were also predicted by the interaction between books read and attendance in the course. Figure 1 shows the interaction between our predictors. For average attendance, there was a significant increase in grades when reading more books, $\beta=.36$, $t(36) = 2.48, p=.02, pr^2 = .15$. For low attendance, there was a non-significant difference in scores when reading more books, $\beta=-.80$, $t(36) = -1.42, p=.16, pr^2 = .05$. Finally, high attending participants showed the largest increase when reading more books, $\beta=1.51$, $t(36) = 2.64, p=.01$, $pr^2 =.16$.

[include SPSS figure]