









<ul> <li>PROCESS v2 I Patchwork m 1 and 4.</li> </ul>	nas limited features odifications were ad	for dealing dded in upd	with mul ates over	ticategor the year	rical variabl rs only for n	es. nodels
<ul> <li>In version 3, multicategor</li> </ul>	X (causal anteceden ical with up to nine	it) and mod categories i	erators <i>V</i> n <b>any</b> mo	V and Z c odel PRO	an be CESS can	210
estimate, usi preprogramr	ng the <b>mcx, mcw</b> , a ned (indicator, sequ	ential, Helm	nert, effe	ct).	ing systems	are
estimate, usi preprogramr If you don't l own system	ng the <b>mcx, mcw</b> , a ned (indicator, sequ ike the preprogram with the <b>xcatcode, v</b>	nd/or <b>mc2</b> c ential, Helm med coding vcatcode, a	systems, nd <b>zcatco</b>	ct). you can ode optic	program yo ns. For exa	ur mple:
estimate, usi preprogramr If you don't l own system	ng the <b>mcx, mcw</b> , a ned (indicator, sequ ike the preprogram with the <b>xcatcode, v</b>	nd/or <b>mc2</b> c ential, Helm ned coding <b>vcatcode</b> , a X1	systems, nd zcatco	you can ode optic	program yc ns. For exa	our mple:
estimate, usi preprogramr If you don't l own system	ng the <b>mcx, mcw</b> , a ned (indicator, sequ ike the preprogram with the <b>xcatcode, v</b> <u>Group 1</u>	ndy of <b>mc2</b> c ential, Helm med coding <b>vcatcode</b> , a <u><b>X1</b></u> -0.5	systems, nd zcatco <u>x2</u> -0.5	you can you can ode optic	program yc ns. For exa	our mple:
estimate, usi preprogramr If you don't I own system	ng the <b>mcx, mcw</b> , a ned (indicator, sequ ike the preprogramm with the <b>xcatcode, v</b> Group 1 Group 2	ndy of <b>mc2</b> c ential, Helm med coding <b>vcatcode</b> , a <u><b>X1</b></u> -0.5 -0.5	systems, nd zcatco <u>x2</u> -0.5 0.5	you can ode optic X3 0	program yc ns. For exa	our mple:
estimate, usi preprogramr If you don't I own system	ng the <b>mcx, mcw</b> , a ned (indicator, sequ ike the preprogramm with the <b>xcatcode, v</b> Group 1 Group 2 Group 3	ndy of <b>mc2</b> c ential, Helm med coding <b>vcatcode</b> , a <b>X1</b> -0.5 -0.5 0.5	systems, nd zcatco <u>x2</u> -0.5 0.5 0	you can ode optic X3 0 -0.5	program yc ns. For exa	our mple:







********************** OUTCOME VARIABL liking	******** E:	******	*******	*******	******	*****	
Model Summary							
R .5355	R-sq .2868	MS .824	E 1 5 8.176	e df1 6.0000	df2 df2	P .0000	
Model							
c	oeff	se	t	р	LLCI	ULCI	
constant 5.	2977	1.0696	4.9529	.0000	3.1803	7.4151	
X1 -2.	7441	1.3929	-1.9701	.0511	-5.5016	.0133	
x2 -2.	7189	1.2924	-2.1038	.0375	-5.2774	1605	
respappr .	3668	.0720	5.0969	.0000	.2243	.5092	
sexism	2785	.1910	-1.4581	.1474	6565	.0996	
Int_1 . Int_2 .	5426 5086	.2714 .2564	1.9992 1.9839	.0478	.0053	1.0799 1.0162	
Product terms k Int_1 : Int_2 :	ey: X1 X2	x x	sexism sexism				
Test(s) of high	est orden	r uncondi	tional inter	action(s):			
R2-chng X*W .0298	2.54	F 79 2.	df1 0000 122.0	df2 0000 .0	р )824		
Focal predi Mod v	ct: prote ar: sexis	est (X) sm (W)					
Conditional eff	ects of t	the focal	predictor a	at values of	the modera	tor(s):	
(These are also	the rela	ative con	ditional di	ect effects	s of X on Y)		
Moderator value sexism 4.33	(s): 32						
Effect	se	2	t	p LI	LCI UL	CI	
	2057	7 –1 3	289 18	864 - 97	783 19	24	
x13930	.295						



****	*****	** DIRECT AND	INDIRE	CT EFFECTS (	OF X ON Y **	******	****
Rela	tive conditi	onal direct e	effect(s)	) of X on Y			
	sexism	Effect	se	t	р	LLCI	ULCI
X1	4.3332	3930	.2957	-1.3289	.1864	9783	.1924
X1	5.1170	.0323	.2184	.1479	.8826	4001	.4648
X1	5.9007	.4576	.3138	1.4580	.1474	1637	1.0789
X2	4.3332	5149	.2781	-1.8519	.0665	-1.0654	.0355
X2	5.1170	1163	.2298	5061	. 6137	5712	.3386
X2	5.9007	.2824	. 3302	.8551	. 3942	3713	.9361
Rela	tive conditi	onal indirect	effects	s of X on Y			
INDI	RECT EFFECT:						
pro	test ->	respappr	->	liking			
	sexism	Effect	BootSE	BootLLCI	BootULCI		
X1	4.3332	.1694	.1494	1267	. 4714		
X1	5.1170	.4505	.1288	.2198	. 7228		
X1	5.9007	.7316	.2042	.3558	1.1536		
	Index of m	oderated medi	lation:				
	Inde	x BootSE	BootL	LCI BootU	LCI		
sexi	.sm .358	.1585	.01	719 .6	920		
	sexism	Effect	BootSE	BootLLCI	BootULCI		
X2	4.3332	.3946	.1433	.1435	. 6994		
X2	5.1170	.6056	.1488	.3325	.9137		
X2	5.9007	.8165	.2236	.4108	1.2840		
	Index of m	oderated medi	lation:				
	Inde	x BootSE	BootL	LCI BootU	LCI		
sexi	.sm .269	.1462	.00	.5	715		
****	*********	****** ANALS	SIS NOTE	ES AND ERROR	RS ********	*****	****
Leve	l of confide	nce for all o	confidence	ce interval:	s in output:		





## Bootstrapping

- Bootstrap confidence intervals are generated automatically for indirect effects and the index of moderated mediation. The default is 5,000 bootstrap samples, percentile method only. Bias-corrected confidence intervals are not available in v3.
- The bootstrapping algorithm has been enhanced to detect singularities more reliably and replace bootstrap samples when this happens. A new **maxboot** option makes sure that PROCESS doesn't get stuck and never returns to you.
- Bootstrap inference is now available for all regression coefficients defining a model, not just for indirect effects.

