

Universidad Nacional Autónoma de México

Instituto de Investigaciones en Matemáticas Aplicadas y en Sistemas

ESPECIALIZACIÓN EN ESTADÍSTICA APLICADA

Modelos de Ecuaciones Estructurales

Adicción juvenil y padres alcohólicos

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11 de junio de 2021





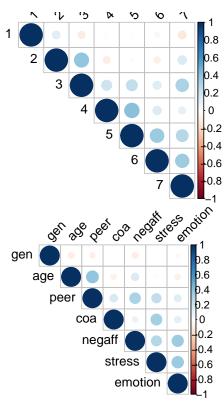
El Proyecto para el Desarrollo de la familia y el adolescente (The Adolescente and FAmily Development Project, en los Estados Unidos) diseñó una investigación que tiene por objetivo "evaluar la asociación entre el alcoholismo de los padres y el uso de sustancias en adolescentes y psicopatologías" (Zamora, 2021). Para tal propósito, se levantó una muestra aleatoria integrada por 316 adolescentes. Adempás, la muestra es compuesta íntegramente por variables medidas, por lo que se realiza un Análisis de Trayectoria (o Path Analysis), lo cuál requiere que haya teorías y conceptos de área que respalden la investigación.

Específicamente, se parte de la siguiente teorización. Los padres alcohólicos (coa) inciden en vidas con efectos estresantes (stress) para las y los hijos, lo que aumenta la percepción de depresión y ansiedad en los adolescentes (negaff). Además, se considera que las familias alcoholicas provoca en los jóvenes falta de control emocional (emotion), lo que incrementa depresión y ansiedad (negaff) en estos últimos. Entonces, se podría argüir que eventos estresantes (stress) tiene una relación no direccional con falta de control emocional (emotion). En complemento a lo anterior, los resutlados negativos, como ansiedad y depresión, generan tasas altas de convivencia con compañeros que consumen drogas (peer), lo que podría generar adicciones. Finalmente, se considera que el estres (stres) y la dificultad emocional (emotion) son predichas por la edad (age) y el sexo (gen).

A continuación se muestra una tabla con el *nombre de variables*, sus *siglas*, a manera de codificación, y las variables que representan.

Dado que se cuenta con la base de datos se procede a hacer estadística descriptiva. Todas las variables son numéricas, pero coa y gen son variables dicotómias, donde $P(X|x_{coa}=0:Padresnoalcoholicos)$, y $P(X|x_{gen}=0:Mujer)$, respectivamente. Además, las variables, Stress, emotion, negaff y peer son variables continuas, que parecen ser tasas o índices, ya que tienen valores positivos y menores de 6. Cabe destacar que no se cuenta con un diccionario de datos.

A continuación se muestran dos correlogramas. Cabe señalar que no hay ninguna correlación significativa. El primer correlograma integra a las correlaciones biserial, tetracórica y de pearson. Mientras que el segundo sólamente usa la última correlación. Se evidencia, que las correlaciones para variables dicotómicas aumentaron (es decir, se intensificó su color).







1. Diagramar modelo

```
CorMid <- '
1.0
-0.09456621 1.0
0.01400000 0.12159467
0.41430068 -0.01973430 -0.01121133 1.0
0.14398422 -0.08074436 -0.04854675 0.3664796 1.0
0.10279496 \quad 0.15121667 \quad -0.12520711 \quad 0.2807905 \quad 0.35387788 \ 1.0
0.20542024 \quad 0.39572236 \quad -0.10289694 \quad 0.2402493 \quad 0.13368237 \quad 0.3145978 \quad 1.0989694 \quad 0.2402493 \quad 0.2
\# corCuad <- matrix(data = c(c(1, -0.09456621, 0.014, 0.41430068, 0.14398422, 0.10279496, 0.20542024),
                                                 c(-0.09456621, 1, 0.12159467, -0.01973430, -0.08074436, 0.15121667, 0.39572236),
#
                                                 c(0.014,\ 0.12159467,\ 1,\ -0.01121133,\ -0.04854675,\ -0.12520711,\ -0.10289694),
#
                                                 c(0.41430068, -0.01973430 , -0.01121133, 1, 0.3664796, 0.2807905, 0.2402493),
                                                 c(0.14398422, -0.08074436, -0.04854675, 0.3664796, 1, 0.35387788, 0.13368237),
#
#
                                                 c(0.10279496, 0.15121667, -0.12520711, 0.2807905, 0.35387788, 1, 0.3145978),
#
                                                 c(0.20542024, 0.39572236, -0.10289694,0.2402493 , 0.13368237, 0.3145978, 1)
#
                                                 ),7,7)
comp.cor1 <- getCov(CorMid, sds = NULL, names = c("coa", "age", "gen", "stress", "emotion", "negaff", "</pre>
#Modelo teórico
mod1 <- '
stress ~ a*coa + b*gen + c*age
emotion ~ e*coa + f*gen + g*age
negaff ~ x*stress + y*emotion
peer ~ z*negaff
emotion ~~ stress
coa ~~ gen
gen ~~ age
coa ~~ age
#Efectos indirectos
NegStresCoa := x*a
NegStresGen := x*b
NegStresAge := x*c
NegEmoCoa := y*e
NegEmoGen := y*f
NegEmoAge := y*g
PeNegStresCoa := z*x*a
PeNegEmoCoa := z*y*e
#Efetos Totales
T1 := a + x*a + z*x*a
T2 := a + y*e + z*y*e
n <- length(bd$coa)</pre>
sem1 <- sem(mod1, data = bd, sample.cov = comp.cor1, sample.nobs = n, se="bootstrap")</pre>
sem2 <- sem(mod1, data = bd, sample.cov = personc, sample.nobs = n, se="bootstrap")</pre>
```





summary(sem1, fit.measures = TRUE, standardized=T)

## ##	lavaan 0.6-8 ended normally after 31 itera	ations
##	Estimator	ML
##	Optimization method	NLMINB
##	Number of model parameters	20
##		
##	Number of observations	316
##		
##	Model Test User Model:	
##		
##	Test statistic	81.173
##	Degrees of freedom	8
##	P-value (Chi-square)	0.000
##		
##	Model Test Baseline Model:	
##		
##	Test statistic	255.823
##	Degrees of freedom	21
##	P-value	0.000
##		
##	User Model versus Baseline Model:	
##		
##	Comparative Fit Index (CFI)	0.688
##	Tucker-Lewis Index (TLI)	0.182
##		
	Loglikelihood and Information Criteria:	
##	I1-1-1-1-1 11-1 (IIO)	0170 100
##	Loglikelihood user model (H0)	-2179.133
##	Loglikelihood unrestricted model (H1)	-2138.547
##	Akaike (AIC)	4398.267
##	Bayesian (BIC)	4473.382
##	Sample-size adjusted Bayesian (BIC)	4409.947
##	bampie bize dajabted bayebidi (bio)	1100.011
	Root Mean Square Error of Approximation:	
##		
##	RMSEA	0.170
##	90 Percent confidence interval - lower	0.138
##	90 Percent confidence interval - upper	0.205
##	P-value RMSEA <= 0.05	0.000
##		
##	Standardized Root Mean Square Residual:	
##		
##	SRMR	0.095
##		
##	Parameter Estimates:	
##		
##	Standard errors	Bootstrap
##	Number of requested bootstrap draws	1000
##	Number of successful bootstrap draws	1000
##		





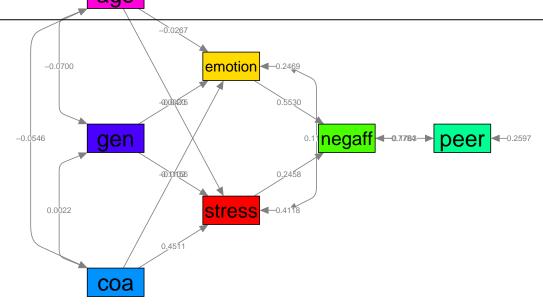
## stress -	##	## Regressions:							
## coa (a) 0.451 0.075 5.999 0.000 0.451 0.331 ## gen (b) -0.016 0.073 -0.214 0.831 -0.016 -0.011 ## age (c) 0.002 0.026 0.077 -0.214 0.831 -0.016 -0.011 ## emotion -	##			Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
## gen (b) -0.016 0.073 -0.214 0.831 -0.016 -0.011 ## age (c) 0.002 0.026 0.077 0.939 0.002 0.004 ## emotion	##	stress ~							
## age	##	coa	(a)	0.451	0.075	5.999	0.000	0.451	0.331
## coa (e) 0.110 0.057 1.946 0.052 0.110 0.101 ## gen (f) -0.048 0.057 -0.833 0.405 -0.048 -0.047 ## age (g) -0.027 0.022 -1.209 0.227 -0.027 -0.077 ## negaff - ## stress (x) 0.246 0.094 2.628 0.009 0.246 0.175 ## emotion (y) 0.553 0.115 4.819 0.000 0.553 0.290 ## peer - ## negaff (z) 0.176 0.032 5.550 0.000 0.176 0.315 ## ## Covariances: ## age	##	gen	(b)	-0.016	0.073	-0.214	0.831	-0.016	-0.011
## coa (e) 0.110 0.057 1.946 0.052 0.110 0.110 ## gen (f) -0.048 0.057 -0.833 0.405 -0.048 -0.047 ## age (g) -0.027 0.022 -1.209 0.227 -0.027 -0.077 ## negaff - ## stress (x) 0.246 0.094 2.628 0.009 0.246 0.175 ## emotion (y) 0.553 0.115 4.819 0.000 0.553 0.290 ## peer - ## negaff (z) 0.176 0.032 5.550 0.000 0.176 0.315 ## coarriances: ## Covariances: ## coa ## gen 0.012 0.018 6.187 0.000 0.112 0.352 ## gen ## age 0.000 0.014 0.157 0.875 0.002 0.009 ## gen ## age 0.005 0.041 0.157 0.875 0.002 0.009 ## coa ## age 0.005 0.041 0.157 0.875 0.002 0.009 ## coa ## age 0.005 0.041 0.157 0.875 0.005 0.009 ## writing age 0.006 0.040 0.178 0.078 0.070 0.097 ## coa ## age 0.005 0.041 0.157 0.875 0.005 0.009 ## coa ## age 0.005 0.041 0.1347 0.178 0.070 0.097 ## coa ## age 0.005 0.041 0.1347 0.178 0.055 0.076 ## ## writing age 0.002 0.004 0.000 0.000 0.412 0.890 ## ## ## coa ## age 0.042 0.002 0.004 0.0369 0.000 0.412 0.890 ## ## ## ## coa 0.249 0.002 0.014 0.000 0.249 0.009 ## age 0.0249 0.002 141.501 0.000 0.249 0.009 ## age 0.0249 0.002 161.599 0.000 0.249 1.000 ## age 0.0249 0.002 161.590 0.000 0.249 1.000 ## age 0.0249 0.002 161.590 0.000 0.249 1.000 ## age 0.0249 0.002 161.590 0.000 0.249 1.000 ## RegStresCoa 0.111 0.046 0.230 0.015 0.111 0.058 ## NegStresCoa 0.111 0.046 0.034 0.055 0.015 0.111 0.058 ## NegStresCoa 0.016 0.034 0.001 0.943 0.000 0.001 ## NegEmoCoa 0.061 0.034 1.785 0.015 0.111 0.058 ## NegEmoCoa 0.061 0.034 1.785 0.010 0.001 0.001 ## NegEmoCoa 0.061 0.034 1.785 0.010 0.038 0.000 0.001 ## PeNegEmoCoa 0.061 0.034 1.785 0.000 0.523 0.033 ## PeNegEmoCoa 0.061 0.034 0.035 0.038 0.000 0.052 0.001 ## PeNegEmoCoa 0.061 0.034 1.785 0.000 0.523 0.037 ## PeNegEmoCoa 0.061 0.034 0.035 0.000 0.523 0.037 ## PeNegEmoCoa 0.061 0.034 0.035 0.000 0.523 0.037	##	age	(c)	0.002	0.026	0.077	0.939	0.002	0.004
## gen (f) -0.048 0.057 -0.833 0.405 -0.048 -0.047 ## age (g) -0.027 0.022 -1.209 0.227 -0.027 -0.077 ## areaff	##	emotion ~							
## negaff - ## stress (x) 0.246 0.094 2.628 0.009 0.227 -0.027 -0.077 ## peer - ## peer - ## megaff (z) 0.176 0.032 5.550 0.000 0.553 0.290 ## peer - ## stress (x) 0.246 0.094 2.628 0.009 0.246 0.175 ## peer - ## negaff (z) 0.176 0.032 5.550 0.000 0.176 0.315 ## ## Covariances: ## Estimate Std.Err z-value P(> z) Std.lv Std.all ## .stress ## .emotion 0.112 0.018 6.187 0.000 0.112 0.352 ## gen	##	coa	(e)	0.110	0.057	1.946	0.052	0.110	0.110
## stress (x) 0.246 0.094 2.628 0.009 0.246 0.175 ## emotion (y) 0.553 0.115 4.819 0.000 0.553 0.290 ## peer - ## negaff (z) 0.176 0.032 5.550 0.000 0.176 0.315 ## ## Covariances: ## covariances: ## stress ## gen	##	gen	(f)	-0.048	0.057	-0.833	0.405	-0.048	-0.047
## stress (x) 0.246 0.094 2.628 0.009 0.246 0.175 ## emotion (y) 0.553 0.115 4.819 0.000 0.553 0.290 ## peer ~ ## negaff (z) 0.176 0.032 5.550 0.000 0.176 0.315 ## ## Covariances: ## c.motion 0.112 0.018 6.187 0.000 0.112 0.352 ## gen 0.002 0.014 0.157 0.875 0.002 0.009 ## gen ~ ## age 0.000 0.040 0.176 0.078 0.078 0.000 0.012 ## coa ~ ## age 0.005 0.041 0.157 0.875 0.002 0.009 ## coa ~ ## age 0.005 0.041 0.157 0.875 0.002 0.009 ## coa ~ ## age 0.005 0.041 0.157 0.875 0.002 0.009 ## coa ~ ## age 0.005 0.041 0.157 0.875 0.000 0.009 ## coa ~ ## age 0.005 0.041 0.157 0.875 0.000 0.009 ## coa ~ ## age 0.000 0.040 0.076 0.078 0.078 0.070 0.097 ## .stress 0.412 0.040 10.369 0.000 0.412 0.890 ## .stress 0.412 0.040 10.369 0.000 0.412 0.890 ## .negaff 0.778 0.017 14.537 0.000 0.247 0.979 ## .negaff 0.078 0.017 14.537 0.000 0.247 0.979 ## .negaff 0.078 0.017 14.537 0.000 0.247 0.979 ## .peer 0.260 0.032 8.001 0.000 0.260 0.901 ## gen 0.249 0.002 141.501 0.000 0.260 0.901 ## age 0.249 0.002 141.501 0.000 0.249 1.000 ## gen 0.249 0.002 146.99 0.000 0.249 1.000 ## gen 0.249 0.002 146.99 0.000 0.249 1.000 ## gen 0.249 0.002 146.99 0.000 0.249 1.000 ## age 0.000 0.000 0.000 0.000 0.000 0.000 ## megstresCoa 0.111 0.046 0.430 0.015 0.011 0.000 ## NegStresGen 0.004 0.019 0.0201 0.841 0.000 0.001 ## NegStresGen 0.004 0.019 0.0201 0.841 0.000 0.001 ## NegStresAge 0.000 0.007 0.071 0.943 0.000 0.001 ## NegEmoGoa 0.061 0.034 1.785 0.074 0.061 0.002 ## NegEmoGoa 0.061 0.034 1.785 0.074 0.061 0.002 ## NegEmoGoa 0.061 0.034 1.785 0.074 0.061 0.002 ## PeNegEmoCoa 0.001 0.007 1.633 0.003 0.011 0.010 ## T1 0.582 0.106 5.643 0.000 0.523 0.373 ## *summary(modelo, fit.measures = TRUE, standardized=T) ## #resumen <- summary(modelo, fit.measures = TRUE, standardized=T) ## #resumen <- summary(modelo, fit.measures = TRUE, standardized=T) ## #resumen <- summary(modelo, fit.measures = TRUE, standardized=T)	##	age	(g)	-0.027	0.022	-1.209	0.227	-0.027	-0.077
## emotion (y) 0.553 0.115 4.819 0.000 0.553 0.290 ## peer	##	negaff ~							
## peer	##	stress	(x)	0.246	0.094	2.628	0.009	0.246	0.175
##	##	emotion	(y)	0.553	0.115	4.819	0.000	0.553	0.290
## Covariances: ## Covariances: ## Estimate Std.Err z-value P(> z) Std.1v Std.al1 ## .emotion 0.112 0.018 6.187 0.000 0.112 0.352 ## coa ~- ## gen 0.002 0.014 0.157 0.875 0.002 0.009 ## gen ~- ## age -0.070 0.040 -1.763 0.078 -0.070 0.097 ## coa ~- ## wage -0.055 0.041 -1.347 0.178 -0.055 0.002 0.009 ## variances: ## Variances: ## Stimate Std.Err z-value P(> z) Std.1v Std.al1 ## .emotion 0.247 0.017 11.002 0.000 0.247 0.979 ## .negaff 0.778 0.071 11.002 0.000 0.247 0.979 ## gen 0.260 0.032 8.001 0.000 0.247 0.991 ## gen 0.249 0.002 141.501 0.000 0.260 0.901 ## age 2.095 0.124 16.922 0.000 0.249 1.000 ## age 2.095 0.124 16.922 0.000 0.249 1.000 ## age 2.095 0.124 16.922 0.000 2.095 1.000 ## NegStresGoa 0.111 0.046 2.430 0.015 0.111 0.058 ## NegStresGoa 0.111 0.046 2.430 0.015 0.111 0.058 ## NegStresGoa 0.061 0.034 1.785 0.071 0.943 0.000 ## NegStresGoa 0.061 0.034 1.785 0.074 0.061 0.032 ## NegStresGoa 0.061 0.034 1.785 0.074 0.061 0.032 ## NegEmoGoa 0.011 0.007 1.633 0.003 0.015 0.011 0.010 ## NegEmoCoa 0.011 0.007 1.633 0.003 0.011 0.010 ## PeNegEmoCoa 0.011 0.007 1.633 0.003 0.011 0.010 ## T1 0.582 0.006 5.463 0.000 0.582 0.407 ## zummary(modelo, fit.measures = TRUE, standardzed=T) ## summary(modelo, fit.measures = TRUE, standardzed=T) ## #resumen <- summary(modelo, fit.measures = TRUE, standardzed=T)	##	peer ~							
## Covariances: ##	##	negaff	(z)	0.176	0.032	5.550	0.000	0.176	0.315
## .stress ## .emotion	##	-							
## .stress ~~ ## coa ~~ ## gen	##	Covariances:							
## coa ~~ ## gen	##			Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
## coa ~~ ## gen	##	.stress ~~							
## coa ~~ ## gen	##	.emotion		0.112	0.018	6.187	0.000	0.112	0.352
## age	##	coa ~~							
## age	##	gen		0.002	0.014	0.157	0.875	0.002	0.009
## age	##								
## coa ~~ ## age		•		-0.070	0.040	-1.763	0.078	-0.070	-0.097
##	##								
##	##	age		-0.055	0.041	-1.347	0.178	-0.055	-0.076
## summary (modelo, fit.measures = TRUE, standardized=T) ## stress	##	J							
## .stress									
## .emotion	##			Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
## .negaff 0.778 0.071 11.002 0.000 0.778 0.848 ## .peer 0.260 0.032 8.001 0.000 0.260 0.901 ## coa 0.249 0.002 141.501 0.000 0.249 1.000 ## gen 0.249 0.002 106.199 0.000 0.249 1.000 ## age 2.095 0.124 16.922 0.000 2.095 1.000 ## Defined Parameters: ## Estimate Std.Err z-value P(> z) Std.lv Std.all ## NegStresCoa 0.111 0.046 2.430 0.015 0.111 0.058 ## NegStresGen -0.004 0.019 -0.201 0.841 -0.004 -0.002 ## NegStresAge 0.000 0.007 0.071 0.943 0.000 0.001 ## NegEmoCoa 0.061 0.034 1.785 0.074 0.061 0.032 ## NegEmoGen -0.026 0.033 -0.801 0.423 -0.026 -0.014 ## NegEmoAge -0.015 0.012 -1.255 0.210 -0.015 -0.022 ## PeNegStresCoa 0.020 0.009 2.078 0.038 0.020 0.018 ## PeNegEmoCoa 0.011 0.007 1.633 0.103 0.011 0.010 ## T1 0.582 0.106 5.463 0.000 0.582 0.407 ## T2 0.523 0.094 5.543 0.000 0.523 0.373	##	.stress		0.412	0.040	10.369	0.000	0.412	0.890
## .peer 0.260 0.032 8.001 0.000 0.260 0.901 ## coa 0.249 0.002 141.501 0.000 0.249 1.000 ## gen 0.249 0.002 106.199 0.000 0.249 1.000 ## age 2.095 0.124 16.922 0.000 2.095 1.000 ## ## Defined Parameters: ## Defined Parameters: ## NegStresCoa 0.111 0.046 2.430 0.015 0.111 0.058 ## NegStresGen -0.004 0.019 -0.201 0.841 -0.004 -0.002 ## NegStresAge 0.000 0.007 0.071 0.943 0.000 0.001 ## NegEmoCoa 0.061 0.034 1.785 0.074 0.061 0.032 ## NegEmoGen -0.026 0.033 -0.801 0.423 -0.026 -0.014 ## NegEmoAge -0.015 0.012 -1.255 0.210 -0.015 -0.022 ## PeNegEmoCoa 0.020 0.009 2.078 0.038 0.020 0.018 ## PeNegEmoCoa 0.011 0.007 1.633 0.103 0.011 0.010 ## T1 0.582 0.106 5.463 0.000 0.582 0.407 ## T2 0.523 0.094 5.543 0.000 0.523 0.373 ## # summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T)	##	.emotion			0.017	14.537	0.000	0.247	0.979
## .peer 0.260 0.032 8.001 0.000 0.260 0.901 ## coa 0.249 0.002 141.501 0.000 0.249 1.000 ## gen 0.249 0.002 106.199 0.000 0.249 1.000 ## age 2.095 0.124 16.922 0.000 2.095 1.000 ## ## Defined Parameters: ## Defined Parameters: ## NegStresCoa 0.111 0.046 2.430 0.015 0.111 0.058 ## NegStresGen -0.004 0.019 -0.201 0.841 -0.004 -0.002 ## NegStresAge 0.000 0.007 0.071 0.943 0.000 0.001 ## NegEmoCoa 0.061 0.034 1.785 0.074 0.061 0.032 ## NegEmoGen -0.026 0.033 -0.801 0.423 -0.026 -0.014 ## NegEmoAge -0.015 0.012 -1.255 0.210 -0.015 -0.022 ## PeNegEmoCoa 0.020 0.009 2.078 0.038 0.020 0.018 ## PeNegEmoCoa 0.011 0.007 1.633 0.103 0.011 0.010 ## T1 0.582 0.106 5.463 0.000 0.582 0.407 ## T2 0.523 0.094 5.543 0.000 0.523 0.373 ## # summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T)									
## coa 0.249 0.002 141.501 0.000 0.249 1.000 ## gen 0.249 0.002 106.199 0.000 0.249 1.000 ## age 2.095 0.124 16.922 0.000 2.095 1.000 ## ## Defined Parameters: ## Estimate Std.Err z-value P(> z) Std.lv Std.all ## NegStresCoa 0.111 0.046 2.430 0.015 0.111 0.058 ## NegStresGen -0.004 0.019 -0.201 0.841 -0.004 -0.002 ## NegStresAge 0.000 0.007 0.071 0.943 0.000 0.001 ## NegEmoCoa 0.061 0.034 1.785 0.074 0.061 0.032 ## NegEmoGen -0.026 0.033 -0.801 0.423 -0.026 -0.014 ## NegEmoAge -0.015 0.012 -1.255 0.210 -0.015 -0.022 ## PeNegEmoAge -0.015 0.012 -1.255 0.210 -0.015 -0.022 ## PeNegEmoCoa 0.001 0.007 1.633 0.103 0.011 0.010 ## T1 0.582 0.106 5.463 0.000 0.582 0.407 ## T2 0.523 0.094 5.543 0.000 0.523 0.373 ## summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T)									
## gen		-							
## age 2.095 0.124 16.922 0.000 2.095 1.000 ## ## Defined Parameters: ## Defined Parameters: ## NegStresCoa 0.111 0.046 2.430 0.015 0.111 0.058 ## NegStresGen -0.004 0.019 -0.201 0.841 -0.004 -0.002 ## NegStresAge 0.000 0.007 0.071 0.943 0.000 0.001 ## NegEmoCoa 0.061 0.034 1.785 0.074 0.061 0.032 ## NegEmoGen -0.026 0.033 -0.801 0.423 -0.026 -0.014 ## NegEmoAge -0.015 0.012 -1.255 0.210 -0.015 -0.022 ## PeNegStresCoa 0.020 0.009 2.078 0.038 0.020 0.018 ## PeNegEmoCoa 0.011 0.007 1.633 0.103 0.011 0.010 ## T1 0.582 0.106 5.463 0.000 0.582 0.407 ## T2 0.523 0.094 5.543 0.000 0.523 0.373 ## *summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T)									
## Defined Parameters: ## Defined Parameters: ## Estimate Std.Err z-value P(> z) Std.lv Std.all ## NegStresCoa 0.111 0.046 2.430 0.015 0.111 0.058 ## NegStresGen -0.004 0.019 -0.201 0.841 -0.004 -0.002 ## NegStresAge 0.000 0.007 0.071 0.943 0.000 0.001 ## NegEmoCoa 0.061 0.034 1.785 0.074 0.061 0.032 ## NegEmoGen -0.026 0.033 -0.801 0.423 -0.026 -0.014 ## NegEmoAge -0.015 0.012 -1.255 0.210 -0.015 -0.022 ## PeNegStresCoa 0.020 0.009 2.078 0.038 0.020 0.018 ## PeNegEmoCoa 0.011 0.007 1.633 0.103 0.011 0.010 ## T1 0.582 0.106 5.463 0.000 0.582 0.407 ## T2 0.523 0.094 5.543 0.000 0.523 0.373 ## summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T)		-							
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## NegStresGen					Std.Err	z-value	P(> z)	Std.lv	Std.all
## NegStresGen -0.004 0.019 -0.201 0.841 -0.004 -0.002 ## NegStresAge 0.000 0.007 0.071 0.943 0.000 0.001 ## NegEmoCoa 0.061 0.034 1.785 0.074 0.061 0.032 ## NegEmoGen -0.026 0.033 -0.801 0.423 -0.026 -0.014 ## NegEmoAge -0.015 0.012 -1.255 0.210 -0.015 -0.022 ## PeNegStresCoa 0.020 0.009 2.078 0.038 0.020 0.018 ## PeNegEmoCoa 0.011 0.007 1.633 0.103 0.011 0.010 ## T1 0.582 0.106 5.463 0.000 0.582 0.407 ## T2 0.523 0.094 5.543 0.000 0.523 0.373 ## # summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T)	##	NegStresCoa	a	0.111					
## NegStresAge 0.000 0.007 0.071 0.943 0.000 0.001 ## NegEmoCoa 0.061 0.034 1.785 0.074 0.061 0.032 ## NegEmoGen -0.026 0.033 -0.801 0.423 -0.026 -0.014 ## NegEmoAge -0.015 0.012 -1.255 0.210 -0.015 -0.022 ## PeNegStresCoa 0.020 0.009 2.078 0.038 0.020 0.018 ## PeNegEmoCoa 0.011 0.007 1.633 0.103 0.011 0.010 ## T1 0.582 0.106 5.463 0.000 0.582 0.407 ## T2 0.523 0.094 5.543 0.000 0.523 0.373 ## # summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T)		_							
## NegEmoCoa 0.061 0.034 1.785 0.074 0.061 0.032 ## NegEmoGen -0.026 0.033 -0.801 0.423 -0.026 -0.014 ## NegEmoAge -0.015 0.012 -1.255 0.210 -0.015 -0.022 ## PeNegStresCoa 0.020 0.009 2.078 0.038 0.020 0.018 ## PeNegEmoCoa 0.011 0.007 1.633 0.103 0.011 0.010 ## T1 0.582 0.106 5.463 0.000 0.582 0.407 ## T2 0.523 0.094 5.543 0.000 0.523 0.373 ## # summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T)		_							
## NegEmoGen									
## NegEmoAge		•							
## PeNegStresCoa 0.020 0.009 2.078 0.038 0.020 0.018 ## PeNegEmoCoa 0.011 0.007 1.633 0.103 0.011 0.010 ## T1 0.582 0.106 5.463 0.000 0.582 0.407 ## T2 0.523 0.094 5.543 0.000 0.523 0.373 # # summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T)									
## PeNegEmoCoa 0.011 0.007 1.633 0.103 0.011 0.010 ## T1 0.582 0.106 5.463 0.000 0.582 0.407 ## T2 0.523 0.094 5.543 0.000 0.523 0.373 ## summary(modelo, fit.measures = TRUE, standardized=T) ##resumen <- summary(modelo, fit.measures = TRUE, standardized=T)			Coa						
## T1 0.582 0.106 5.463 0.000 0.582 0.407 ## T2 0.523 0.094 5.543 0.000 0.523 0.373 # # summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T)									
## T2 0.523 0.094 5.543 0.000 0.523 0.373 # # summary (modelo, fit.measures = $TRUE$, $standardized=T$) # #resumen <- summary (modelo, fit.measures = $TRUE$, $standardized=T$)		•							
<pre># # summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T)</pre>									
<pre># summary(modelo, fit.measures = TRUE, standardized=T) # #resumen <- summary(modelo, fit.measures = TRUE, standardized=T)</pre>				· -					
<pre># #resumen <- summary(modelo, fit.measures = TRUE, standardized=T)</pre>			£ ; ‡		- TRIE of		A-T)		
· · · · · · · · · · · · · · · · · · ·									
# J'ilmeasures(moaelo)				•	ıt.measur	es = IKUE	,stanaard	ızea=1)	
	#]	iimeasures(mod	elo)						





semPaths(sem1, "mod", "par", col=rainbow(7), style="lisrel", layout = "tree2", curve=1.5, curvePivot = TRU
legend("topleft", legend=c("Consumo sustancia por padres alcohlicos y psicopatologías"), col="blue", cex=

Consumo sustancia por padres alcohlicos y psicopato



2. Escribirlo matricialmente

$$\begin{split} Y_{stres} &= 0Y_{stres} + 0Y_{emo} + 0Y_{neg} + 0Y_{peer} + \gamma_{1,1}X_{coa} + \gamma_{1,2}X_{gen} + \gamma_{1,3}X_{age} + \varsigma_{1} \\ Y_{emo} &= 0Y_{stres} + 0Y_{emo} + 0Y_{neg} + 0Y_{peer} + \gamma_{2,1}X_{coa} + \gamma_{2,2}X_{gen} + \gamma_{2,3}X_{age} + \varsigma_{2} \\ Y_{neg} &= \beta_{1,1}Y_{stres} + \beta_{1,2}Y_{emo} + 0Y_{neg} + 0Y_{peer} + 0X_{coa} + 0X_{gen} + 0X_{age} + \varsigma_{3} \\ Y_{emo} &= 0Y_{stres} + 0Y_{emo} + \beta_{2,1}Y_{neg} + + 0Y_{peer} + 0X_{coa} + 0X_{gen} + 0X_{age} + \varsigma_{4} \\ \end{split}$$

$$\begin{bmatrix} Y_{stre} \\ Y_{emo} \\ Y_{neg} \\ Y_{peer} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ \beta_{1,1} & \beta_{1,2} & 0 & 0 \\ 0 & 0 & \beta_{2,1} & 0 \end{bmatrix} \begin{bmatrix} Y_{stre} \\ Y_{emo} \\ Y_{neg} \\ Y_{peer} \end{bmatrix} + \begin{bmatrix} \gamma_{1,1} & \gamma_{1,2} & \gamma_{1,3} \\ \gamma_{2,1} & \gamma_{2,2} & \gamma_{2,3} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} X_{coa} \\ X_{gen} \\ X_{age} \end{bmatrix} + \begin{bmatrix} \varsigma_1 \\ \varsigma_2 \\ \varsigma_3 \\ \varsigma_4 \end{bmatrix}$$

3. Escribir matrices involucradas en modelo

Además, respéctivamente, cada matriz presentada con anterioridad puede se expresada como: $Y = BY + \Gamma x + \zeta \setminus$



$$\boldsymbol{\Psi} = \begin{bmatrix} \psi_{1,1} & 0 & 0 & 0 \\ \psi_{2,1} & \psi_{2,2} & 0 & 0 \\ 0 & 0 & \psi_{3,1} & 0 \\ 0 & 0 & 0 & \psi_{4,1} \end{bmatrix} \boldsymbol{\Phi} = \begin{bmatrix} \phi_{1,1} & 0 & 0 \\ \phi_{2,1} & \phi_{2,2} & 0 \\ \phi_{3,1} & \phi_{3,2} & \phi_{3,3} \end{bmatrix}$$

Cabe destacar que Ψ representa la matriz de correlación entre variables endógenas (Y_i) . Mientras que la matriz de Φ presenta a la correlación entre variables exógenas (X_i) .

4. Ajuste del modelo

##

##

##

Comparative Fit Index (CFI)

Tucker-Lewis Index (TLI)

La estimación del modelo emplea el método bootstrap, como alternativa a las restricciones del supuesto de normalidad por el método delta. Lo anterior requiere que la muestra esté disponible para realizar el remuestreo (Hallquist, 2019).

Además, se emplean la paquetería *lavaan* como principal instrumento de ajuste computaciones, y se usa la información de la matriz de correlación de Pearson, biserial y tetracórica, según corresponda el tipo de variable. Se tienen 20 grados de libertad, lo que corresponde a las parte de información. A continuación se muestra el código empleado.

```
# CorMid
# comp.cor1 <- qetCov(CorMid, sds = NULL, names = c("coa", "age", "gen", "stress", "emotion", "negaff"
# sem1 <- sem(mod1, data = bd, sample.cov = comp.cor1, sample.nobs = n, se="bootstrap")
summary(sem1, fit.measures = TRUE, standardized=T)
## lavaan 0.6-8 ended normally after 31 iterations
##
##
     Estimator
                                                         ML
##
     Optimization method
                                                     NLMINB
     Number of model parameters
                                                         20
##
##
##
     Number of observations
                                                        316
##
## Model Test User Model:
##
                                                     81.173
##
     Test statistic
     Degrees of freedom
##
##
     P-value (Chi-square)
                                                      0.000
##
## Model Test Baseline Model:
##
                                                    255.823
##
     Test statistic
##
     Degrees of freedom
                                                         21
##
     P-value
                                                      0.000
##
## User Model versus Baseline Model:
##
```

0.688

0.182





## ##	Loglikelihood and Information Criteria:							
##	Loglikelihood user model (HO) -2179.133							
##	_					2173.133		
##	Loglikelihood unrestricted model (H1) -2138.547							
##	Akaike (AIC	:)				4398.267		
##	Bayesian (B					4473.382		
##	Sample-size		ted Baves	ian (BIC)		4409.947		
##	•	3	,					
##	Root Mean Squ	are Er	ror of Ap	proximati	on:			
##								
##	RMSEA					0.170		
##	90 Percent	confid	lence inte	rval - lo	wer	0.138		
##	90 Percent			rval - up	per	0.205		
##	P-value RMS	SEA <=	0.05			0.000		
##					_			
	Standardized	Root M	lean Squar	e Residua	1:			
##	CDMD					0 005		
##	SRMR					0.095		
	Parameter Est	imatas						
##	rarameter Lst	Imates	•					
##	Standard er	rors			В	Sootstrap		
##	Number of r		ed bootst	rap draws		1000		
##	Number of s	_		_		1000		
##				-				
##	Regressions:							
##			Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
##	stress ~							
##	coa	(a)	0.451	0.075		0.000	0.451	0.331
##	gen	(b)	-0.016	0.073				
##	age emotion ~	(c)	0.002	0.026	0.077	0.939	0.002	0.004
##	coa coa	(e)	0.110	0.057	1.946	0.052	0.110	0.110
##	gen	(f)	-0.048	0.057				
##	age	(g)	-0.027	0.022	-1.209	0.227	-0.027	-0.077
##	negaff ~	(6)	0.02.	*****	1,200	****	0.02.	
##	stress	(x)	0.246	0.094	2.628	0.009	0.246	0.175
##	emotion	(y)		0.115			0.553	
##	peer ~							
##	negaff	(z)	0.176	0.032	5.550	0.000	0.176	0.315
##								
	Covariances:							
##			Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
##	.stress ~~		0 440	0.040	0.407	0 000	0 440	0.050
##	.emotion		0.112	0.018	6.187	0.000	0.112	0.352
## ##	coa ~~		0.002	0.014	0.157	0.875	0.002	0.009
##	gen gen ~~		0.002	0.014	0.137	0.075	0.002	0.003
##	age		-0.070	0.040	-1.763	0.078	-0.070	-0.097
##	coa ~~		0.010	0.010	1.700	0.010	0.010	0.001
##	age		-0.055	0.041	-1.347	0.178	-0.055	-0.076
##	J							
##	Variances:							





##		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
##	.stress	0.412	0.040	10.369	0.000	0.412	0.890
##	.emotion	0.247	0.017	14.537	0.000	0.247	0.979
##	.negaff	0.778	0.071	11.002	0.000	0.778	0.848
##	.peer	0.260	0.032	8.001	0.000	0.260	0.901
##	coa	0.249	0.002	141.501	0.000	0.249	1.000
##	gen	0.249	0.002	106.199	0.000	0.249	1.000
##	age	2.095	0.124	16.922	0.000	2.095	1.000
##							
##	Defined Parameters	:					
##		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
##	${\tt NegStresCoa}$	0.111	0.046	2.430	0.015	0.111	0.058
##	NegStresGen	-0.004	0.019	-0.201	0.841	-0.004	-0.002
##	${\tt NegStresAge}$	0.000	0.007	0.071	0.943	0.000	0.001
##	NegEmoCoa	0.061	0.034	1.785	0.074	0.061	0.032
##	NegEmoGen	-0.026	0.033	-0.801	0.423	-0.026	-0.014
##	${\tt NegEmoAge}$	-0.015	0.012	-1.255	0.210	-0.015	-0.022
##	${\tt PeNegStresCoa}$	0.020	0.009	2.078	0.038	0.020	0.018
##	PeNegEmoCoa	0.011	0.007	1.633	0.103	0.011	0.010
##	T1	0.582	0.106	5.463	0.000	0.582	0.407
##	T2	0.523	0.094	5.543	0.000	0.523	0.373

#resumen <- summary(modelo, fit.measures = TRUE, standardized=T)
fitmeasures(sem1)</pre>

##	npar	fmin	chisq	df
##	20.000	0.128	81.173	8.000
##	pvalue	baseline.chisq	baseline.df	baseline.pvalue
##	0.000	255.823	21.000	0.000
##	cfi	tli	nnfi	rfi
##	0.688	0.182	0.182	0.167
##	nfi	pnfi	ifi	rni
##	0.683	0.260	0.705	0.688
##	logl	unrestricted.logl	aic	bic
##	-2179.133	-2138.547	4398.267	4473.382
##	ntotal	bic2	rmsea	rmsea.ci.lower
##	316.000	4409.947	0.170	0.138
##	rmsea.ci.upper	rmsea.pvalue	rmr	rmr_nomean
##	0.205	0.000	0.077	0.077
##	srmr	srmr_bentler	<pre>srmr_bentler_nomean</pre>	crmr
##	0.095	0.095	0.095	0.109
##	crmr_nomean	srmr_mplus	srmr_mplus_nomean	cn_05
##	0.109	0.095	0.095	61.369
##	cn_01	gfi	agfi	pgfi
##	79.210	0.940	0.790	0.269
##	mfi	ecvi		
##	0.891	0.383		

La estimación se los parámetros se muestra a continuación:

5. Verifique lo adecuado del ajuste

A fin de verificar el ajuste del modelo, se deben considerar los índices de bondad de ajuste (GoF, por sus siglas en Inglés).





La prueba de la χ^2 rechaza la hipótesis nula, donde $H_o:ModeloS$ íAjusta, es decir que el modelo no ajusta a los datos. Debido a que el Pvalor es mucho menor que la significancia. Sin embargo, el modelo basal es mucho peor que el propuesto.

User Model:

Test statistic 81.173 Degrees of freedom 8 P-value (Chi-square) 0.000

Model Test Baseline Model:

Test statistic 255.823 Degrees of freedom 21 P-value 0.000

Cuadro 1: Índices de ajuste del modelo

CFI	TLI	RMSEA	Pvalue RMSEA	SRMR
0.688	0.182	0.17	0.0	0.095

- CFI: Es el *Comparative Fit Index*, en que este modelo tiene un valor muy pequeño. Por lo que se puede sostener que el modelo es muy malo. Además, para valores "mayor 0.97 es indicativo de un buen ajuste en relación con el modelo de independencia" (Zamora, 2021).
- NNFI ,también conocido como TLI, es decir, "indice de ajuste no normalizado (NNFI), también conocido como el índice de Tuker-Lewis (TLI)". Este modelo tiene un valor muy pequeño, lo que indica que el modelo es malo. Ya que "valores superiores a 0.95 pueden interpretarse como un ajuste aceptable" (Zamora, 2021).
- RMSEA, significa error cuadrático medio de aproximación de la raíz. Donde valores mayores a 0.1, implican valores de ajuste medriocres, por lo que este modelo no es bueno.
- Pvalur RMSEA, implica que el valor puntual de RMSAE sea contenido por un intervalor de confianza del 95
- SRMR, o indice de la raís del cuadrado medio del residuo estandarizado, "valores de SRMR menores a 0.05 evidencian un buen ajuste y que menores a 0.10 pueden interpretarse como un ajuste aceptable" (Zamora, 2021). Por lo que se puede afirmar que este modelo tiene un ajuste aceptable.

Por lo anterior es posible afirmar que el modelo, en general, no ajusta. Es decir, los datos no respaldan la teoría propuesta. Entonces, se sugiere modificar las relaciones entre variables, siempre y cuando esté mediada por conocimiento de área experta.

Dado lo anterior se propone reestructurar el modelo en función de conocimiento experto. Donde las únicas variables que medien el modelo sean el hecho que los padres sean alcoholicos (coa), su efecto sobre eventos estresantes (stres) y sobre falta de control de emociones (emotion) ambas en los adolescentes. Y la incidencia de las anteriores sobre ansiedad y depresión (negaff), y su vez sobre el consumo de sustancia (peer).

Entonces, la graficación del modelo quedaría como sigue. Respecto a la forma de estimación del modelo sigue los mismo procesos que el anterior modelo. Y a continuación se muestran los índices de bondad de ajute.

```
mod2v <- '
stress ~ a*coa
emotion ~ e*coa
negaff ~ x*stress + y*emotion
peer ~ z*negaff
emotion ~~ stress
'</pre>
```





sem3v <- sem(mod2v, data = bd, sample.cov = comp.cor1, sample.nobs = n, se="bootstrap")
summary(sem3v, fit.measures = TRUE, standardized=T)</pre>

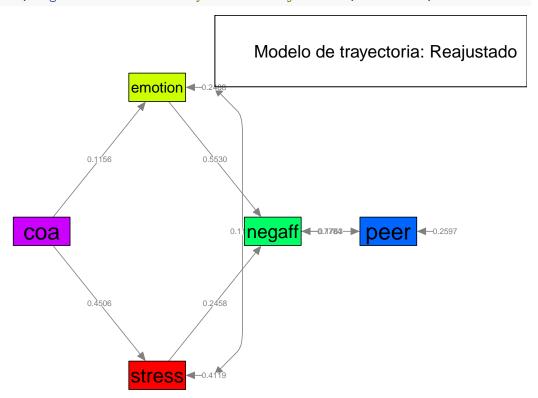
<pre>## lavaan 0.6-8 ended normally after 20 ite ##</pre>	rations
## Estimator	ML
## Optimization method	NLMINB
## Number of model parameters	10
##	
## Number of observations	316
##	
## Model Test User Model:	
##	
## Test statistic	12.267
## Degrees of freedom	4
## P-value (Chi-square)	0.015
##	
## Model Test Baseline Model:	
##	470 077
## Test statistic	179.377
## Degrees of freedom ## P-value	10
## P-value ##	0.000
## User Model versus Baseline Model:	
## User Moder Versus baserine Moder.	
## Comparative Fit Index (CFI)	0.951
## Tucker-Lewis Index (TLI)	0.878
##	0.010
## Loglikelihood and Information Criteria:	
##	
## Loglikelihood user model (HO)	-1160.310
## Loglikelihood unrestricted model (H1)	-1154.176
##	
## Akaike (AIC)	2340.620
## Bayesian (BIC)	2378.177
## Sample-size adjusted Bayesian (BIC)	2346.460
##	
## Root Mean Square Error of Approximation:	
##	
## RMSEA	0.081
## 90 Percent confidence interval - lower	0.032
## 90 Percent confidence interval - upper	
## P-value RMSEA <= 0.05	0.131
<pre>## ## Standardized Root Mean Square Residual:</pre>	
## Standardized Noot Mean Square Residual.	
## SRMR	0.053
##	0.000
## Parameter Estimates:	
##	
## Standard errors	Bootstrap
## Number of requested bootstrap draws	1000
## Number of successful bootstrap draws	1000
##	





```
## Regressions:
                       Estimate Std.Err z-value P(>|z|)
                                                               Std.lv Std.all
##
##
     stress ~
##
                          0.451
                                    0.070
                                             6.432
                                                       0.000
                                                                0.451
                                                                          0.331
                   (a)
       coa
##
     emotion ~
##
                   (e)
                          0.116
                                    0.055
                                             2.084
                                                       0.037
                                                                0.116
                                                                          0.115
       coa
##
     negaff ~
                          0.246
                                    0.093
                                             2.644
                                                       0.008
                                                                0.246
                                                                          0.175
##
       stress
                   (x)
##
       emotion
                   (y)
                          0.553
                                    0.116
                                             4.747
                                                       0.000
                                                                0.553
                                                                          0.290
##
     peer ~
##
       negaff
                   (z)
                          0.176
                                    0.033
                                             5.313
                                                       0.000
                                                                0.176
                                                                          0.315
##
## Covariances:
##
                       Estimate
                                 Std.Err z-value
                                                   P(>|z|)
                                                                        Std.all
                                                               Std.lv
##
    .stress ~~
##
      .emotion
                          0.112
                                    0.018
                                             6.158
                                                       0.000
                                                                0.112
                                                                          0.350
##
##
  Variances:
##
                       Estimate Std.Err z-value P(>|z|)
                                                               Std.lv
                                                                        Std.all
                                    0.040
                                                       0.000
                                                                0.412
                                                                          0.891
##
      .stress
                          0.412
                                            10.266
##
      .emotion
                          0.249
                                    0.017
                                            14.348
                                                       0.000
                                                                0.249
                                                                          0.987
##
      .negaff
                          0.778
                                    0.072
                                            10.842
                                                       0.000
                                                                 0.778
                                                                          0.848
                          0.260
                                    0.032
                                             8.085
                                                       0.000
                                                                0.260
                                                                          0.901
##
      .peer
```

semPaths(sem3v, "mod", "par", col=rainbow(5), style="lisrel", layout = "tree2", curve=1.5, curvePivot = TR legend("topright", legend=c("Modelo de trayectoria: Reajustado"),col="blue",cex=1.1)





6. Interpretar efectos directos, indirectos, totales y concluir

Si se parte del segundo modelo teórico, es posible interpretar los efectos, como se menciona a continuación.