Supplementary material to article 'How to evaluate causal dominance hypotheses in lagged effects models'.

In this supplement, we present the results obtained from simulations. This includes Simulation I, which focuses on bivariate (RI-)CLPM, and Simulation II, which explores the tri-variate (RI-)CLPM. We analyze scenarios where the RI-CLPM did not demonstrate positive random-intercept variances during simulations. Furthermore, we evaluate the performance of the AIC and the GORICA within the context of (RI-)CLPM, specifically focusing on (non-)absolute values of the standardized cross-lagged effects. Furthermore, the comparison between the mean penalty weights and the mean GORICA weights, as well as an assessment of the performance of GORICA and Bayes Factors.

1. Simulation I: bivariate (RI-)CLPM

The number of times the RI-CLPM did not have positive random-intercept variances in a simulation

Table 1. The number of times the RI-CLPM did not have positive random-intercept variances for a combination of simulation conditions (regarding the number of waves, the number of participants, and the cross-lagged effects).

Number of waves	Number of participants	Cross-lagged effects β	Cross-lagged effects γ	Number of times the RI-CLPM did not have positive random-intercept variances
3	25	-0.07	-0.07	5
		0.1	0.2	3
		0.1	0.4	6
	50	0.1	0.2	1
		0.1	0.4	6
	75	0.1	0.4	4
4	25	0.1	0.2	1
		0.1	0.4	2

Note that, only 0.02% of the simulations in the bivariate RI-CLPM resulted in non-positive variance cases, which accounts for 28 times out of a total of 144,000 iterations.

The performance of the AIC in a bivariate (RI-)CLPM

When using the AIC, the informative hypothesis $\beta < \gamma$ is evaluated by comparing the fit of the null hypothesis H_{0a}: $\beta = \gamma$ versus the unconstrained hypothesis Hunc which includes the hypotheses $\beta < \gamma$ and $\beta > \gamma$. Note that in the unequal parameter condition, the unconstrained hypothesis is true, while in the equal parameter condition, both H_{0a} and H_{unc} are correct, although H_{0a} is the most parsimonious one. However, Evaluating H_{0a} versus an unconstrained hypothesis does not answer the question which parameter is the highest. The ability of the AIC to identify the correct hypothesis in a bivariate (RI-)CLPM, considering both non-absolute and absolute values of the standardized cross-lagged effects, is illustrated in Figures 1 to 4.

The performance of the AIC in a bivariate RI-CLPM with absolute values of the standardized cross-lagged effects

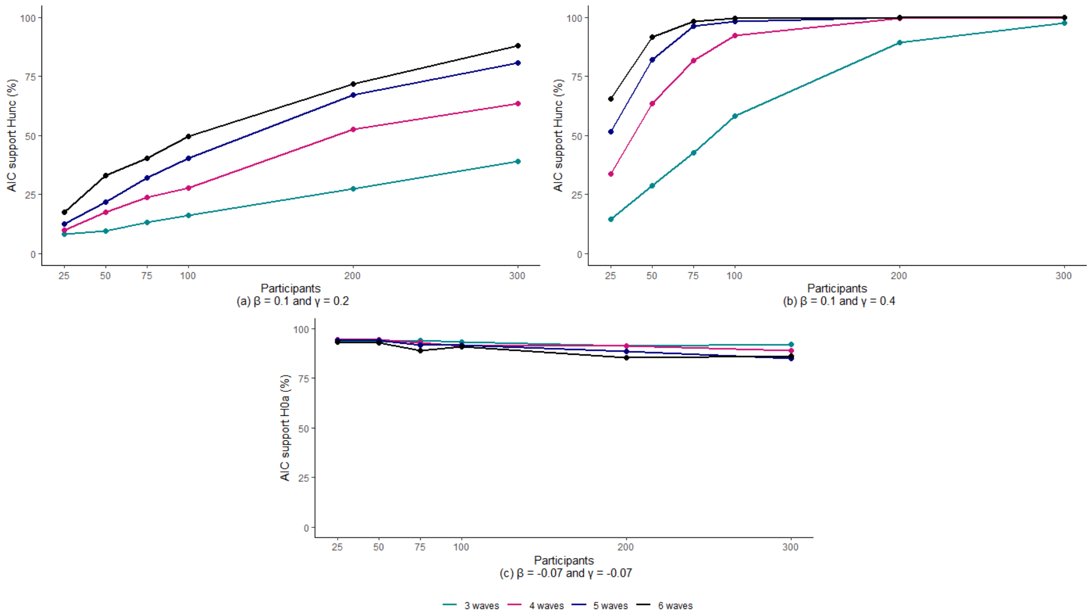


Figure 1. The (true) hypothesis rates when using the AIC in a bivariate RI-CLPM with absolute values of the standardized cross-lagged effects for all simulation conditions, namely the number of participants (x-axis), the number of waves (different colored lines), and the three different pairs of cross-lagged parameters (β and γ): (a) (β, γ) = (0.1, 0.2), (b) (β, γ) = (0.1, 0.4), and (c) (β, γ) = (-0.07, -0.07). Note that in Plots (a) and (b), the unconstrained hypothesis is the true hypothesis, while in Plot (c) both $H_{0a} : \beta = \gamma$ and the unconstrained hypothesis are true but H_{0a} is the most parsimonious one.

The performance of the AIC in a bivariate RI-CLPM with non-absolute values of the standardized cross-lagged effects

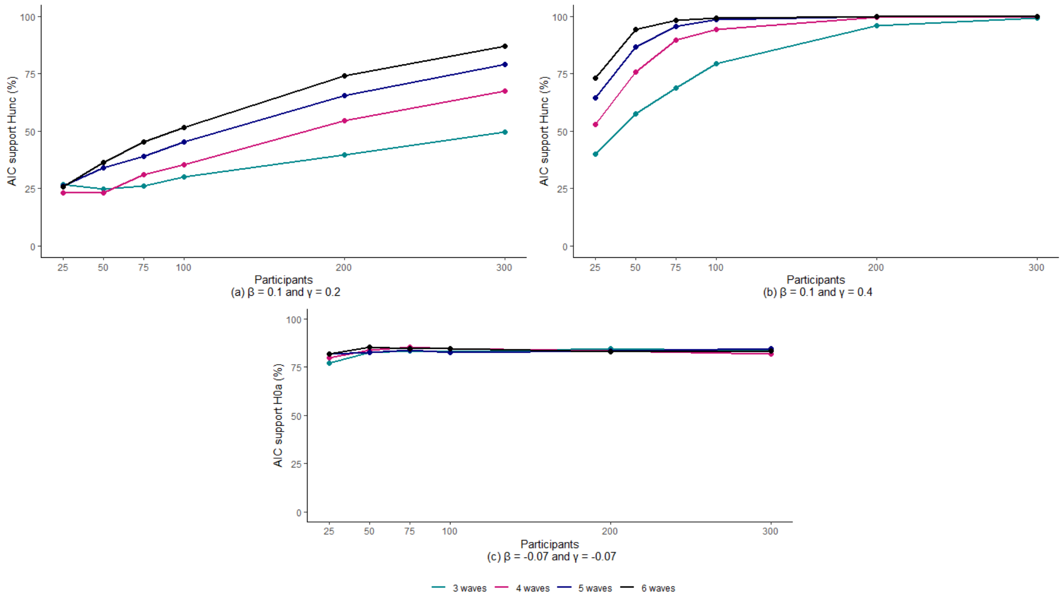


Figure 2. The (true) hypothesis rates of the AIC when using the AIC in a bivariate RI-CLPM with non-absolute values of the standardized cross-lagged effects for all simulation conditions, namely number of participants (x-axis), number of waves (different colored lines), and the three different pairs of cross-lagged parameters (β and γ): (a) (β, γ) = (0.1, 0.2), (b) (β, γ) = (0.1, 0.4), and (c) (β, γ) = (-0.07, -0.07). Note that in Plots (a) and (b), the unconstrained hypothesis is the true hypothesis, while in Plot (c) both H_{0a} and the unconstrained hypothesis are true but H_{0a} is the most parsimonious one.

The performance of the AIC in a bivariate CLPM with absolute values of the standardized cross-lagged effects

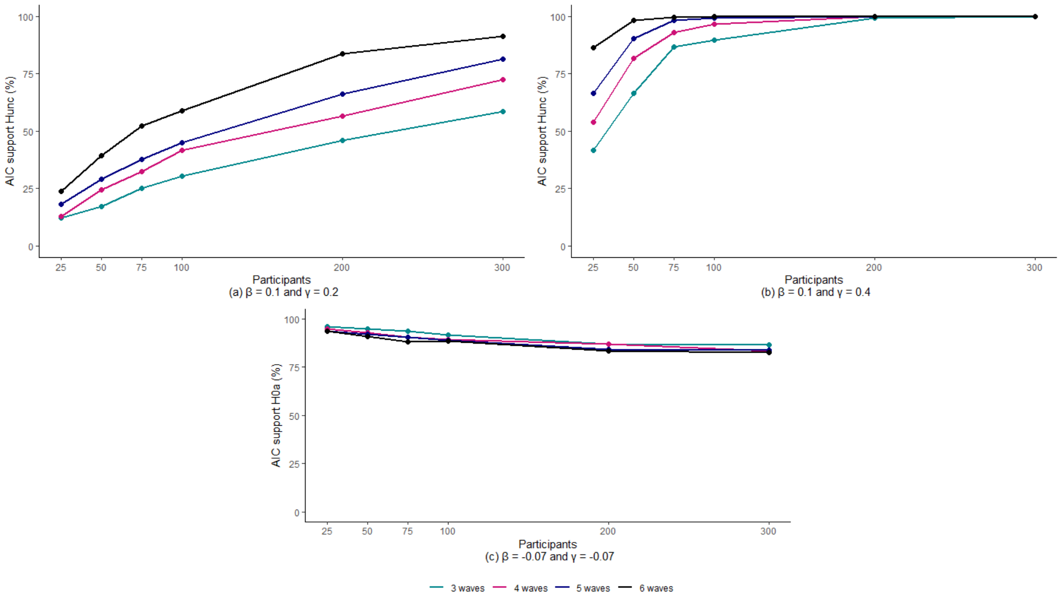


Figure 3. The (true) hypothesis rates of the AIC when using the AIC in a bivariate CLPM with absolute values of the standardized cross-lagged effects for all simulation conditions, namely number of participants (x-axis), number of waves (different colored lines), and the three different pairs of cross-lagged parameters (β and γ): (a) (β, γ) = (0.1, 0.2), (b) (β, γ) = (0.1, 0.4), and (c) (β, γ) = (-0.07, -0.07). Note that in Plots (a) and (b), the unconstrained hypothesis is the true hypothesis, while in Plot (c) both H_{0a} and the unconstrained hypothesis are true but H_{0a} is the most parsimonious one.

The performance of the AIC in a bivariate CLPM with non-absolute values of the standardized cross-lagged effects

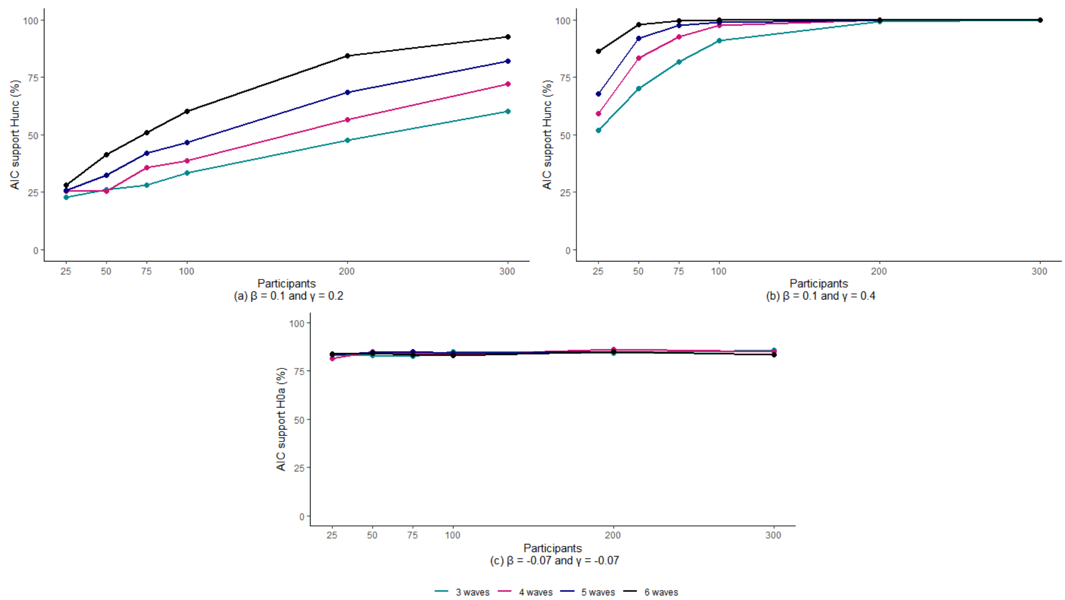


Figure 4. The (true) hypothesis rates of the AIC when using the AIC in a bivariate CLPM with non-absolute values of the standardized cross-lagged effects for all simulation conditions, namely number of participants (x-axis), number of waves (different colored lines), and the three different pairs of cross-lagged parameters (β and γ): (a) (β, γ) = (0.1, 0.2), (b) (β, γ) = (0.1, 0.4), and (c) (β, γ) = (-0.07, -0.07). Note that in Plots (a) and (b), the unconstrained hypothesis is the true hypothesis, while in Plot (c) both H_{0a} and the unconstrained hypothesis are true but H_{0a} is the most parsimonious one.

The performance of the GORICA in a bivariate (RI-)CLPM

The performance of the GORICA in a bivariate RI-CLPM with non-absolute values of the standardized cross-lagged effects

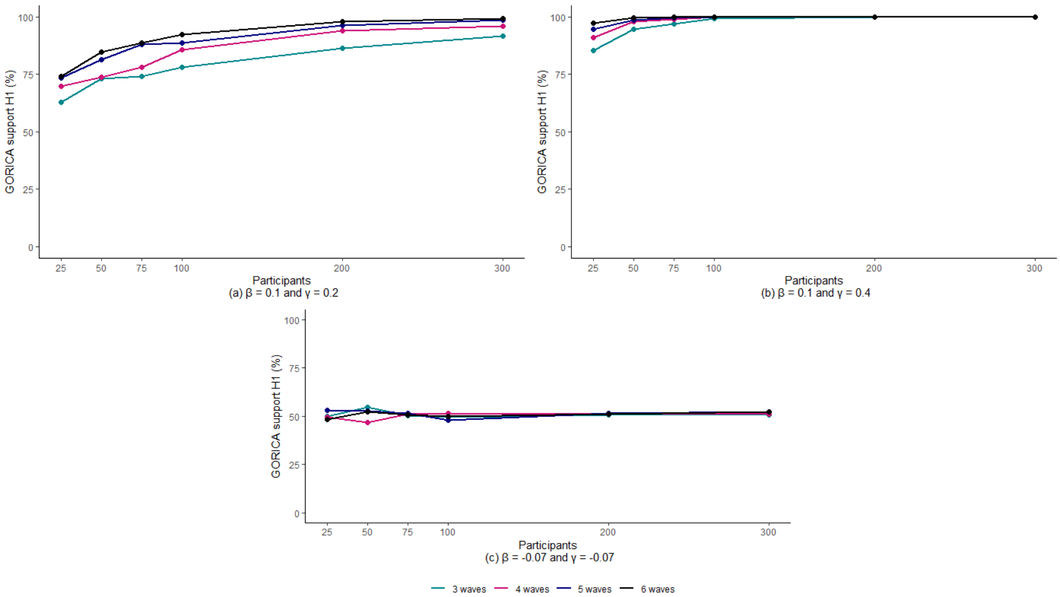


Figure 5. The (true) hypothesis rates of the GORICA when using the GORICA in a bivariate RI-CLPM with non-absolute values of the standardized cross-lagged effects for all simulation conditions, namely number of participants (x-axis), number of waves (different colored lines), and the three different pairs of cross-lagged parameters (β and γ): (a) (β, γ) = (0.1, 0.2), (b) (β, γ) = (0.1, 0.4), and (c) (β, γ) = (-0.07, -0.07). Note that in Plots (a) and (b), H_1 is the true hypothesis, while in Plot (c) both $H_1 : \beta < \gamma$ and $H_2 : \beta > \gamma$ are true.

The performance of the GORICA in a bivariate CLPM with absolute values of the standardized cross-lagged effects

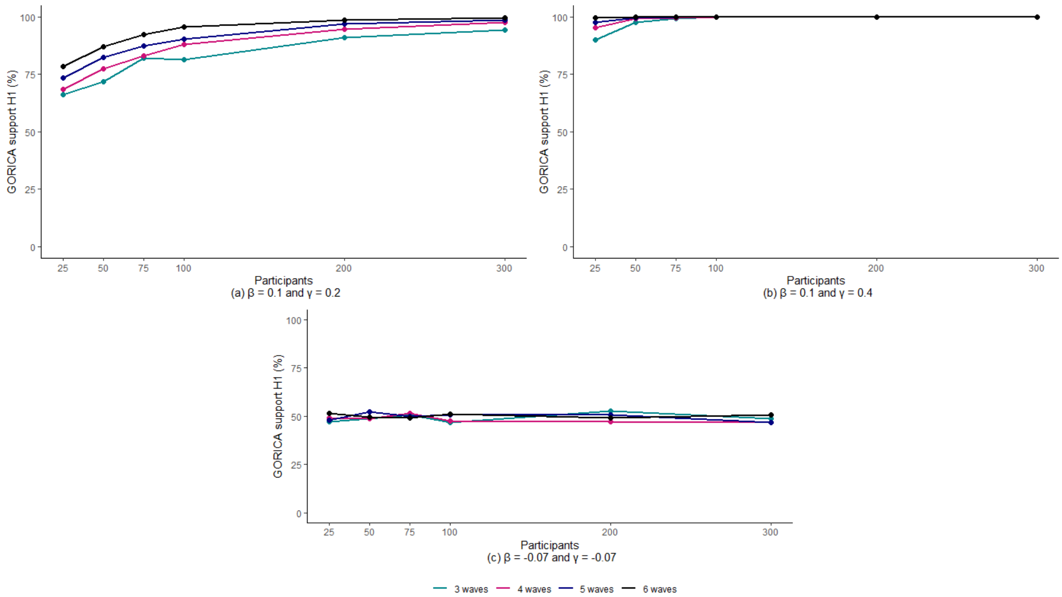


Figure 6. The (true) hypothesis rates of the GORICA when using the GORICA in a bivariate CLPM with absolute values of the standardized cross-lagged effects for all simulation conditions, namely number of participants (x-axis), number of waves (different colored lines), and the three different pairs of cross-lagged parameters (β and γ): (a) (β, γ) = (0.1, 0.2), (b) (β, γ) = (0.1, 0.4), and (c) (β, γ) = (-0.07, -0.07). Note that in Plots (a) and (b), H_1 is the true hypothesis, while in Plot (c) both $H_1 : |\beta| < |\gamma|$ and $H_2 : |\beta| > |\gamma|$ are true.

The performance of the GORICA in a bivariate CLPM with non-absolute values of the standardized cross-lagged effects

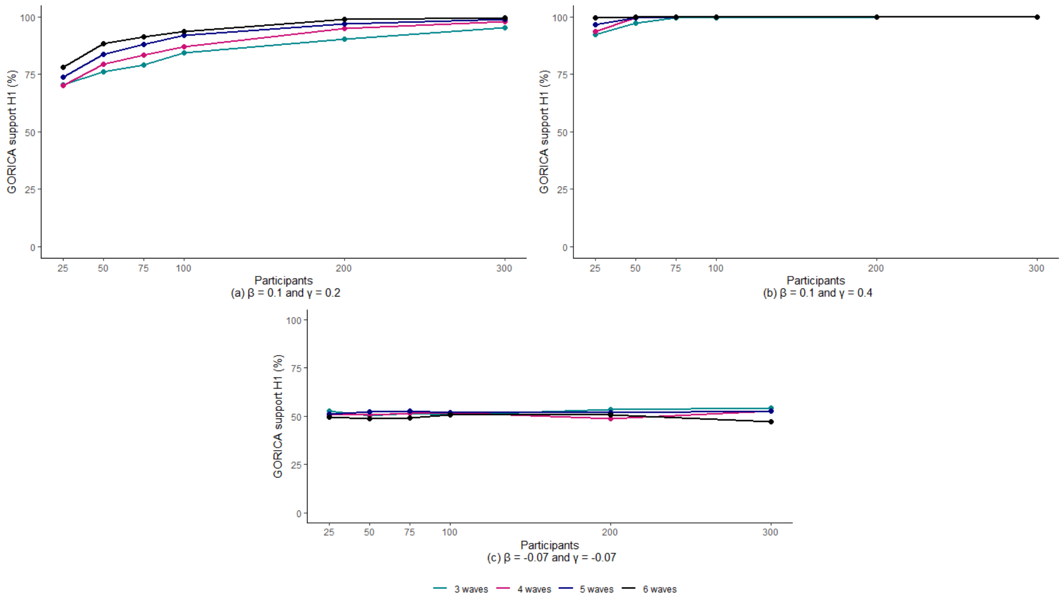


Figure 7. The (true) hypothesis rates of the GORICA when using the GORICA in a bivariate CLPM with non-absolute values of the standardized cross-lagged effects for all simulation conditions, namely number of participants (x-axis), number of waves (different colored lines), and the three different pairs of cross-lagged parameters (β and γ): (a) (β, γ) = (0.1, 0.2), (b) (β, γ) = (0.1, 0.4), and (c) (β, γ) = (-0.07, -0.07). Note that in Plots (a) and (b), H_1 is the true hypothesis, while in Plot (c) both $H_1 : \beta < \gamma$ and $H_2 : \beta > \gamma$ are true.

2. Simulation II: Tri-variate (RI-)CLPM

The number of times the RI-CLPM did not have positive random-intercept variances in a simulation

Table 2. The number of times the RI-CLPM did not have positive random-intercept variances for a combination of simulation conditions (regarding the number of waves, the number of participants, and the cross-lagged effects).

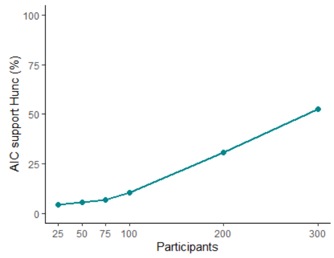
Number of waves	Number of participants	Cross-lagged effects β	Cross-lagged effects γ	Number of times the RI-CLPM did not have positive random-intercept variances
3	25	-0.07	-0.07	2
		0.1	0.2	2
		0.1	0.4	5
	50	0.1	0.4	5
	75	0.1	0.4	10
	100	0.1	0.4	7
	200	0.1	0.4	3

Note that, only 0.09% of the simulations in the tri-variate RI-CLPM resulted in non-positive variance cases, which accounts for 34 times out of a total of 36,000 iterations.

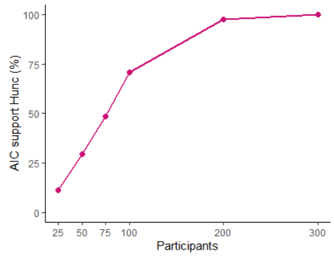
2.1. The performance of the AIC in a tri-ivariate (RI-)CLPM

we assess the performance of the AIC when evaluating causal dominance hypotheses in a tri-variate (RI-)CLPM. However, the AIC is not capable of evaluating inequality constrained hypotheses, we will limit ourselves to the evaluation of the classical null hypothesis $H_{0b} : \phi_{12} = \phi_{21}, \phi_{13} = \phi_{31}, \phi_{23} = \phi_{32}$ versus the unconstrained hypothesis. The performance of the AIC in selecting the true hypothesis within a tri-variate (RI-)CLPM, encompassing both non-absolute and absolute values of the standardized cross-lagged effects, is depicted in Figures 8 to 11.

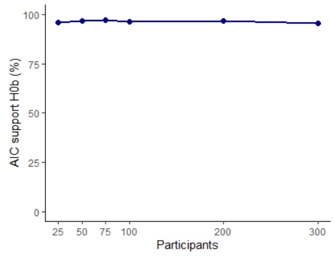
The performance of the AIC in a tri-ivariate RI-CLPM with absolute values of the standardized cross-lagged effects



(a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2)



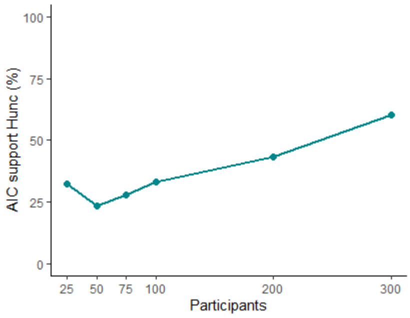
(b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4)



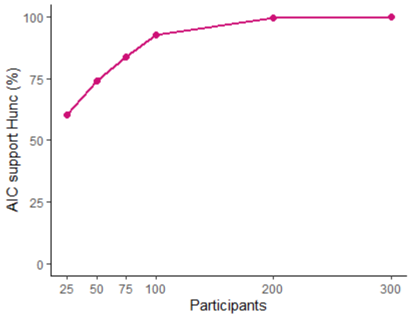
(c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07)

Figure 8. The (true) hypothesis rates when using the AIC in a tri-variate RI-CLPM with absolute values of the standardized cross-lagged effects for all simulation conditions, namely the number of participants (x-axis) and the three different pairs of cross-lagged parameters (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32}): (a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2), (b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4), and (c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07). Note that in Plots (a) and (b), the unconstrained hypothesis is the true hypothesis, while in Plot (c) both H_{0b} and the unconstrained hypothesis are true but H_{0b} is the most parsimonious one.

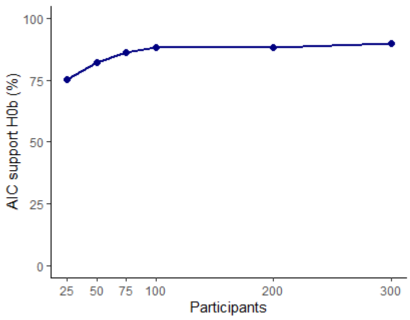
The performance of the AIC in a tri-ivariate RI-CLPM with non-absolute values of the standardized cross-lagged effects



(a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2)



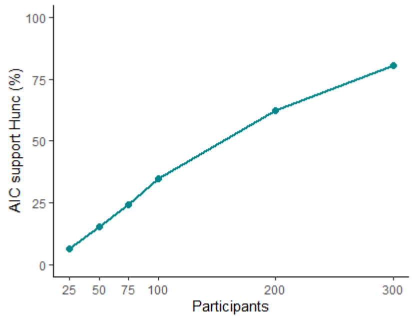
(b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4)



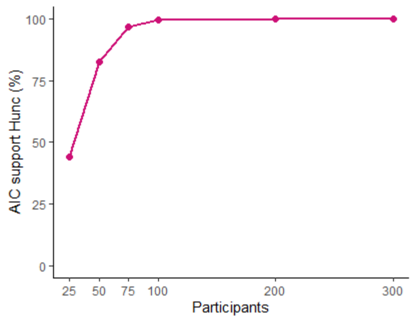
(c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07)

Figure 9. The (true) hypothesis rates of the AIC when using the AIC in a tri-variate RI-CLPM with non-absolute values of the standardized cross-lagged effects for all simulation conditions, namely number of participants (x-axis) and the three different pairs of cross-lagged parameters (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32}): (a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2), (b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4), and (c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07). Note that in Plots (a) and (b), the unconstrained hypothesis is the true hypothesis, while in Plot (c) both H_{0b} and the unconstrained hypothesis are true but H_{0b} is the most parsimonious one.

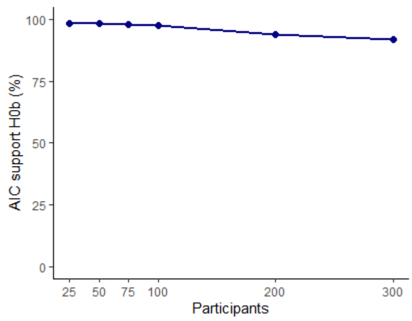
The performance of the AIC in a tri-ivariate CLPM with absolute values of the standardized cross-lagged effects



(a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2)



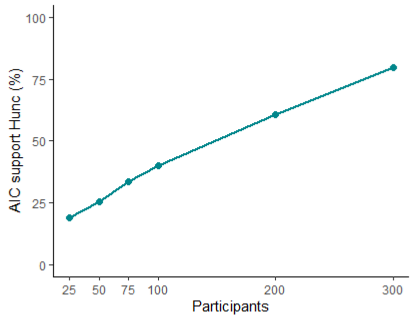
(b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4)



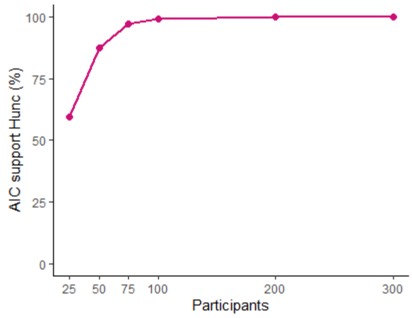
(c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07)

Figure 10. The (true) hypothesis rates of the AIC when using the AIC in a tri-variate CLPM with absolute values of the standardized cross-lagged effects for all simulation conditions, namely number of participants (x-axis) and the three different pairs of cross-lagged parameters (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32}): (a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2), (b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4), and (c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07). Note that in Plots (a) and (b), the unconstrained hypothesis is the true hypothesis, while in Plot (c) both H_{0b} and the unconstrained hypothesis are true but H_{0b} is the most parsimonious one.

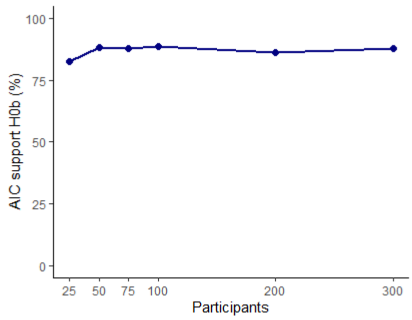
The performance of the AIC in a tri-ivariate CLPM with non-absolute values of the standardized cross-lagged effects



(a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2)



(b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4)

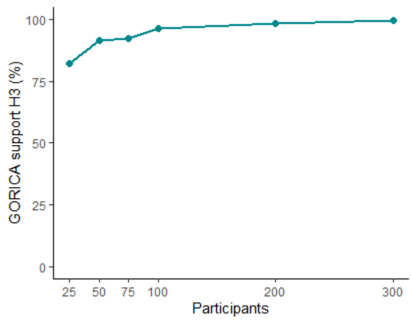


(c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07)

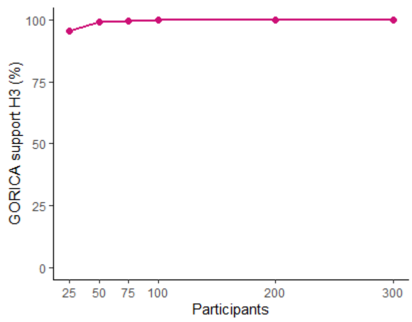
Figure 11. The (true) hypothesis rates of the AIC when using the AIC in a tri-variate CLPM with non-absolute values of the standardized cross-lagged effects for all simulation conditions, namely number of participants (x-axis) and the three different pairs of cross-lagged parameters (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32}): (a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2), (b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4), and (c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07). Note that in Plots (a) and (b), the unconstrained hypothesis is the true hypothesis, while in Plot (c) both H_{0b} and the unconstrained hypothesis are true but H_{0b} is the most parsimonious one.

2.2. *The performance of the GORICA in a tri-variate (RI-)CLPM*

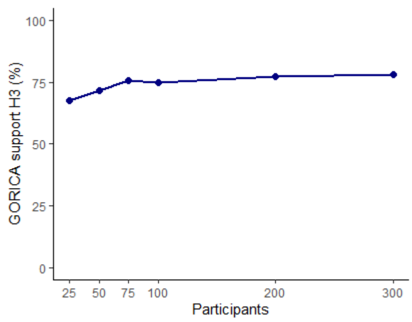
The performance of the GORICA in a tri-variate RI-CLPM with non-absolute values of the standardized cross-lagged effects



(a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2)



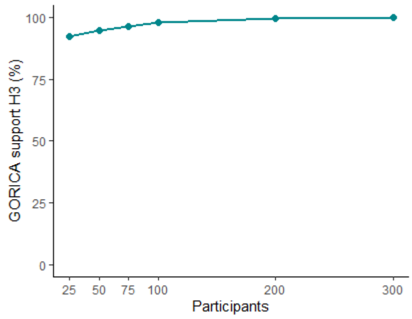
(b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4)



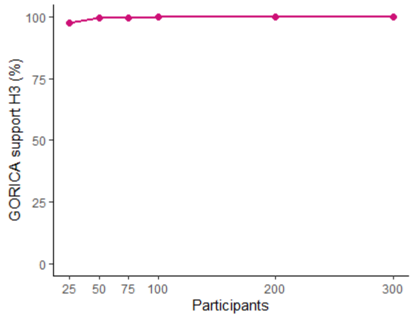
(c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07)

Figure 12. The (true) hypothesis rates of the GORICA when using the GORICA in a tri-variate RI-CLPM with non-absolute values of the standardized cross-lagged effects for all simulation conditions, namely number of participants (x-axis) and the three different pairs of cross-lagged parameters (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32}): (a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2), (b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4), and (c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07). Note that in Plots (a) and (b), H_3 is the true hypothesis, while in Plot (c) both H_3 and its complement are true but H_3 is the most parsimonious one.

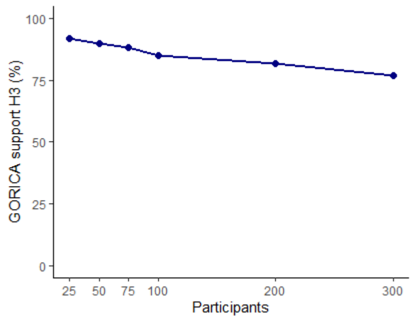
The performance of the GORICA in a tri-variate CLPM with absolute values of the standardized cross-lagged effects



(a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2)



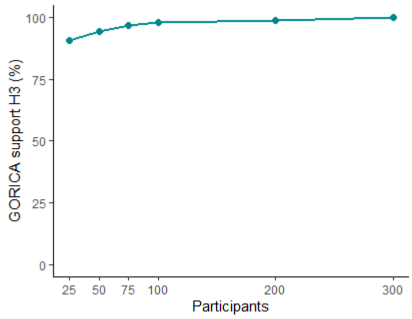
(b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4)



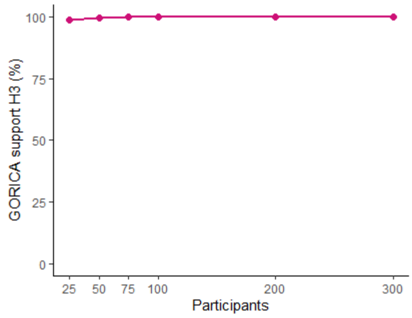
(c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07)

Figure 13. The (true) hypothesis rates of the GORICA when using the GORICA in a tri-variate CLPM with absolute values of the standardized cross-lagged effects for all simulation conditions, namely number of participants (x-axis) and the three different pairs of cross-lagged parameters (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32}): (a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2), (b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4), and (c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07). Note that in Plots (a) and (b), H_3 is the true hypothesis, while in Plot (c) both H_3 and its complement are true but H_3 is the most parsimonious one.

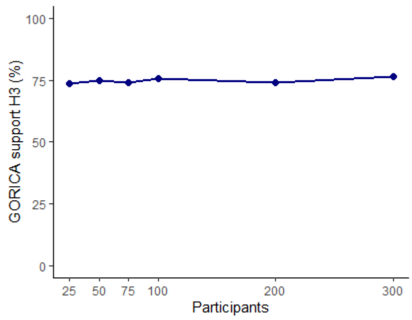
The performance of the GORICA in a tri-variate CLPM with non-absolute values of the standardized cross-lagged effects



(a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2)



(b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4)

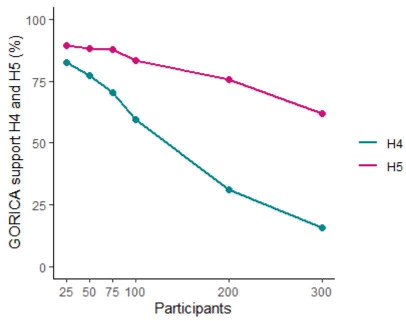


(c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07)

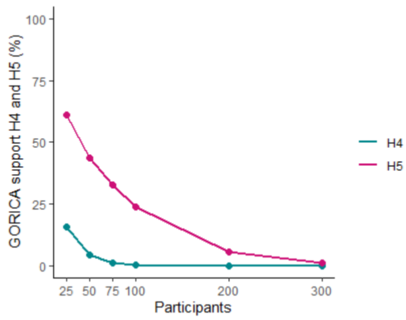
Figure 14. The (true) hypothesis rates of the GORICA when using the GORICA in a tri-variate CLPM with non-absolute values of the standardized cross-lagged effects for all simulation conditions, namely number of participants (x-axis) and the three different pairs of cross-lagged parameters (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32}): (a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2), (b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4), and (c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07). Note that in Plots (a) and (b), H_3 is the true hypothesis, while in Plot (c) both H_3 and its complement are true but H_3 is the most parsimonious one.

3. What if the hypothesis of interest is not true and thus its complement is?

The performance of GORICA in a tri-variate RI-CLPM with non-absolute values of the standardized cross-lagged effects



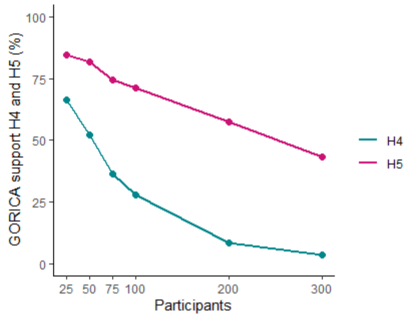
(a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2)



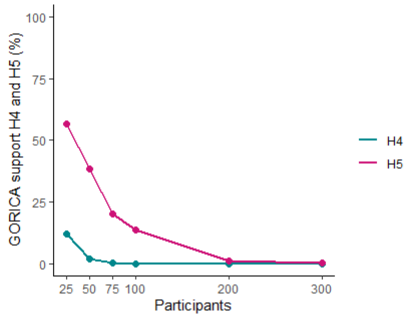
(b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4)

Figure 15. The number of times the incorrect hypotheses H_4 (green) and H_5 (pink) are chosen in a RI-CLPM with non-absolute values of the standardized cross-lagged effects, for various participant numbers (x-axis) and two cross-lagged parameter specifications: (a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2), and (b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4).

The performance of GORICA in a tri-variate CLPM with absolute values of the standardized cross-lagged effects



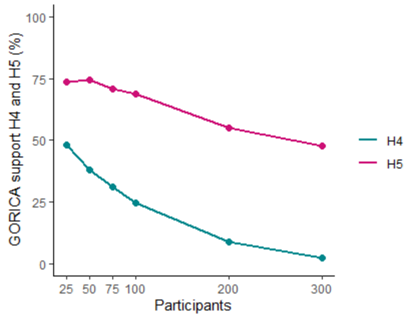
(a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2)



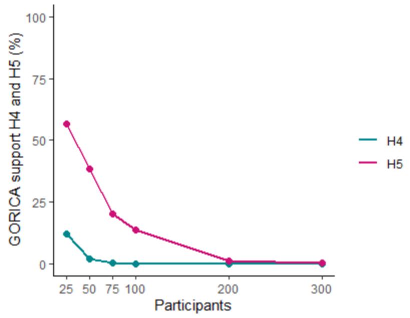
(b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4)

Figure 16. The number of times the incorrect hypotheses H_4 (green) and H_5 (pink) are chosen in a CLPM with absolute values of the standardized cross-lagged effects, for various participant numbers (x-axis) and two cross-lagged parameter specifications: (a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2), and (b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4).

The performance of GORICA in a tri-variate CLPM with non-absolute values of the standardized cross-lagged effects



(a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2)

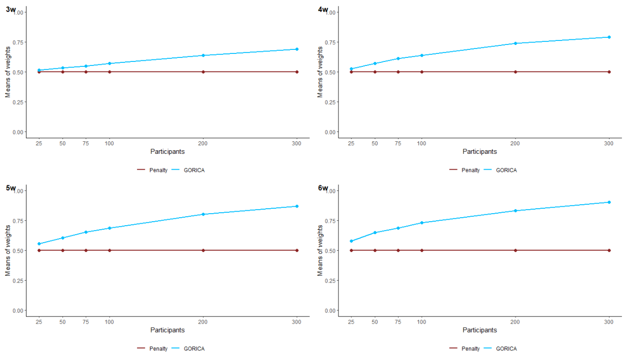


(b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4)

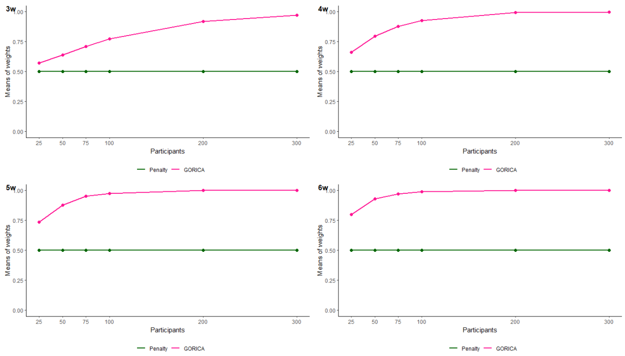
Figure 17. The number of times the incorrect hypotheses H_4 (green) and H_5 (pink) are chosen in a CLPM with non-absolute values of the standardized cross-lagged effects, for various participant numbers (x-axis) and two cross-lagged parameter specifications: (a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2), and (b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4).

4. Mean of the penalty weights and mean of the GORICA weights

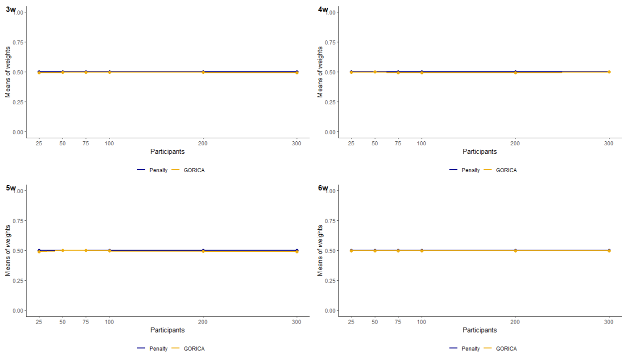
4.1. A bivariate RI-CLPM



(a) β = 0.1, γ = 0.2



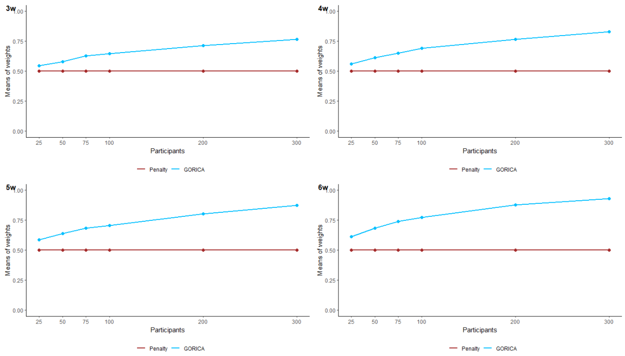
(b) β = 0.1, γ = 0.4



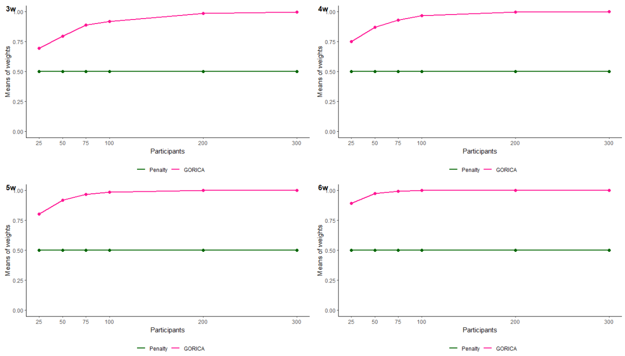
(c) β = -0.07, γ = -0.07

Figure 18. The illustration of the mean of penalty weights and the mean of GORICA weights in a bivariate RI-CLPM regarding different number of waves (w = 3, 4, 5, and 6) and the three different pairs of cross-lagged parameters (β and γ): (a) (β, γ) = (0.1, 0.2), (b) (β, γ) = (0.1, 0.4), and (c) (β, γ) = (-0.07, -0.07).

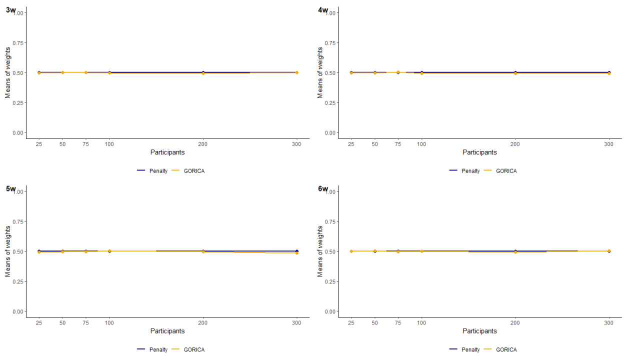
4.2. A bivariate CLPM



(a) β = 0.1, γ = 0.2



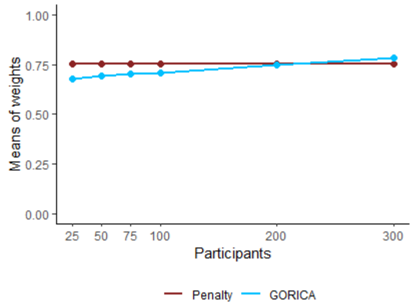
(b) β = 0.1, γ = 0.4



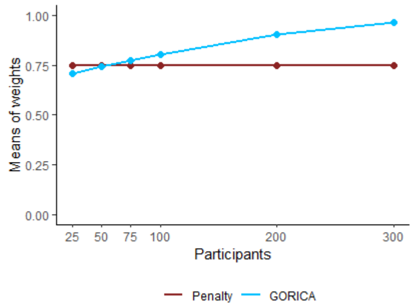
(c) β = -0.07, γ = -0.07

Figure 19. The illustration of the mean of penalty weights and the mean of GORICA weights in a bivariate CLPM regarding different number of waves (w = 3, 4, 5, and 6) and the three different pairs of cross-lagged parameters (β and γ): (a) (β, γ) = (0.1, 0.2), (b) (β, γ) = (0.1, 0.4), and (c) (β, γ) = (-0.07, -0.07).

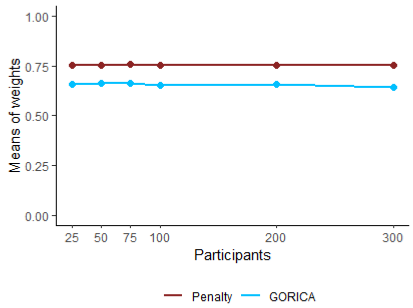
4.3. A tri-variate RI-CLPM



(a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2)



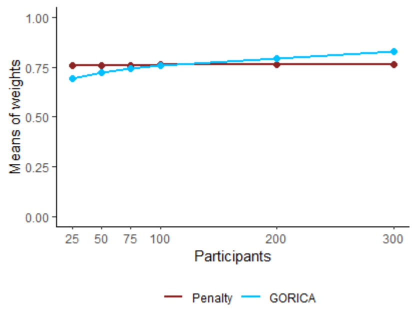
(b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4)



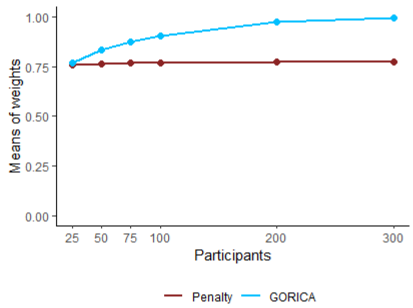
(c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07)

Figure 20. The illustration of the mean of penalty weights and the mean of GORICA weights in a tri-variate RI-CLPM regarding the three different pairs of cross-lagged parameters (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32}): (a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2), (b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4), and (c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07).

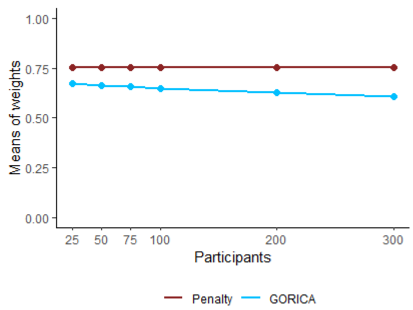
4.4. A tri-variate CLPM



(a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2)



(b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4)



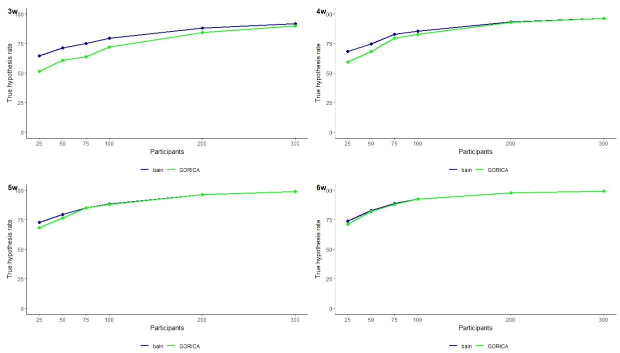
(c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07)

Figure 21. The illustration of the mean of penalty weights and the mean of GORICA weights in a tri-variate CLPM regarding the three different pairs of cross-lagged parameters (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32}): (a) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.2, 0.1, 0.2, 0.1, 0.2), (b) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (0.1, 0.4, 0.1, 0.4, 0.1, 0.4), and (c) (ϕ_{12}, ϕ_{21}, ϕ_{13}, ϕ_{31}, ϕ_{23}, ϕ_{32})= (-0.07, -0.07, -0.07, -0.07, -0.07, -0.07).

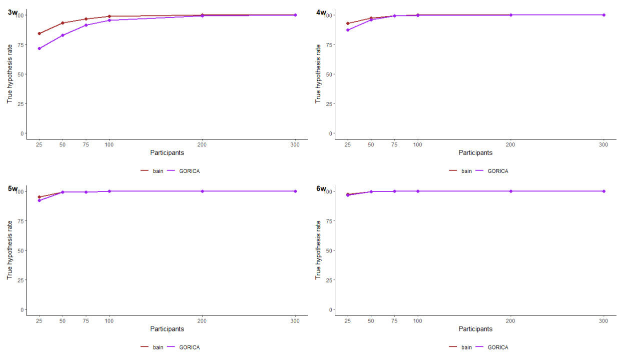
5. The performance of the GORICA and the Bayes Factors (BFs)

We compared the performance of Bayes Factors (BFs) using the *bain* package with that of GORICA. This comparison aimed to evaluate the ability of these techniques to select the correct hypothesis among different pairs of standardized parameter estimates in (RI-)CLPM. Our findings indicate that both Bayes Factors and GORICA consistently yielded similar results across all scenarios.

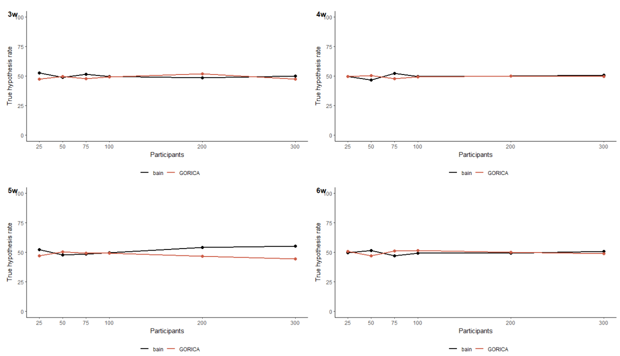
5.1. A bivariate RI-CLPM



(a) β = 0.1, γ = 0.2



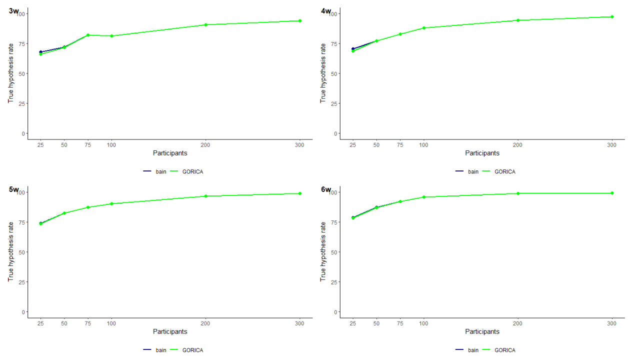
(b) β = 0.1, γ = 0.4



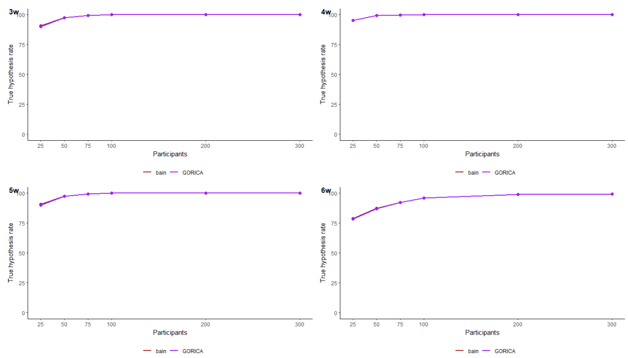
(c) β = -0.07, γ = -0.07

Figure 22. The performance of the GORICA and BFs in a bivariate RI-CLPM regarding different number of waves (w = 3, 4, 5, and 6) and the three different pairs of cross-lagged parameters (β and γ): (a) (β, γ) = (0.1, 0.2), (b) (β, γ) = (0.1, 0.4), and (c) (β, γ) = (-0.07, -0.07).

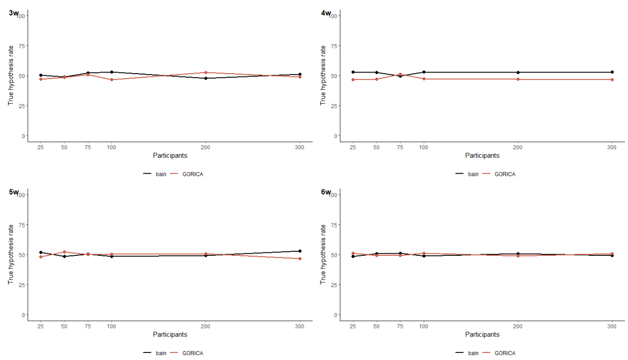
5.2. *A bivariate CLPM*



(a) β = 0.1, γ = 0.2



(b) β = 0.1, γ = 0.4



(c) β = -0.07, γ = -0.07

Figure 23. The performance of the GORICA and BFs in a bivariate CLPM regarding different number of waves (w = 3, 4, 5, and 6) and the three different pairs of cross-lagged parameters (β and γ): (a) (β, γ) = (0.1, 0.2), (b) (β, γ) = (0.1, 0.4), and (c) (β, γ) = (-0.07, -0.07).