

**Online Appendix A: Derivations of the population correspondence between pre-existing three-level MLM  $R^2$  measures and measures from our framework**

Online Appendix A provides derivations showing how the pre-existing three-level MLM  $R^2$  measures listed in Table 2 reflect the same population quantities as measures (or sums of measures) from our framework. This involves replacing terms in the population expression for the pre-existing measures with terms from our model-implied variance expressions that reflect this same quantity in the population. Symbols not defined here were defined in the manuscript. Though all pre-existing measures listed below are equivalent in the population to measures obtained from our framework, some are additionally exactly equivalent in the sample (those not denoted with \*'s below, i.e.,  $R^2_{NSJ(m)}$  and  $R^2_{NSJ(c)}$ ).

**Section A1: Correspondence with Snijders & Bosker's (2012) measure**

The Snijders and Bosker (1999, 2012) measure was defined in manuscript Equation (2) and is reproduced here:

$$R^2_{S\&B} = 1 - \frac{\varphi_{000} + \tau_{000} + \sigma^2}{\varphi_{000(null)} + \tau_{000(null)} + \sigma^2_{(null)}} \tag{OA1}$$

The Snijders and Bosker (2012) approach requires constraining random slope variation to 0, though our framework does not impose this requirement. In the denominator of Equation (OA1), the sum of the random-intercept-only model variance components reflects the total outcome variance. Replacing this expression with our model-implied outcome variance expression in manuscript Equation (9) and simplifying due to having constrained random slope variation to 0 yields

$$\begin{aligned} R^{2*}_{S\&B} &= 1 - \frac{\varphi_{000} + \tau_{000} + \sigma^2}{\gamma'_1 \Phi_1 \gamma_1 + \gamma'_2 \Phi_2 \gamma_2 + \gamma'_3 \Phi_3 \gamma_3 + \varphi_{000} + \tau_{000} + \sigma^2} \\ &= \frac{\gamma'_1 \Phi_1 \gamma_1 + \gamma'_2 \Phi_2 \gamma_2 + \gamma'_3 \Phi_3 \gamma_3 + \varphi_{000} + \tau_{000} + \sigma^2}{\gamma'_1 \Phi_1 \gamma_1 + \gamma'_2 \Phi_2 \gamma_2 + \gamma'_3 \Phi_3 \gamma_3 + \varphi_{000} + \tau_{000} + \sigma^2} \\ &\quad - \frac{\varphi_{000} + \tau_{000} + \sigma^2}{\gamma'_1 \Phi_1 \gamma_1 + \gamma'_2 \Phi_2 \gamma_2 + \gamma'_3 \Phi_3 \gamma_3 + \varphi_{000} + \tau_{000} + \sigma^2} \\ &= \frac{\gamma'_1 \Phi_1 \gamma_1 + \gamma'_2 \Phi_2 \gamma_2 + \gamma'_3 \Phi_3 \gamma_3}{\gamma'_1 \Phi_1 \gamma_1 + \gamma'_2 \Phi_2 \gamma_2 + \gamma'_3 \Phi_3 \gamma_3 + \varphi_{000} + \tau_{000} + \sigma^2} \\ &= R^{2(f_1)}_t + R^{2(f_2)}_t + R^{2(f_3)}_t \end{aligned} \tag{OA2}$$

Again, this holds under Snijders and Boskers' (2012) assumption that random slope variation is 0.

**Section A2: Correspondence with Johnson's (2014) extension of Nakagawa & Schielzeth's (2013) marginal measure**

The linear mixed model version of Johnson's (2014) extension of Nakagawa & Schielzeth's (2013) marginal measure was defined in manuscript Equation (3) and is reproduced here:

$$R^2_{NSJ(m)} = \frac{\sigma_f^2}{\sigma_f^2 + \sigma_{L2}^2 + \sigma_{L3}^2 + \sigma_\epsilon^2} \tag{OA3}$$

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Here, we show the correspondence between each of these terms individually with terms from our model-implied variance expression. Note first that, from the manuscript Appendix A derivation,

$$\begin{aligned}\sigma_f^2 &= \text{var}(\gamma_{000} + \mathbf{x}'_{1ijk}\gamma_1 + \mathbf{x}'_{2jk}\gamma_2 + \mathbf{x}'_{3k}\gamma_3) \\ &= \gamma_1'\Phi_1\gamma_1 + \gamma_2'\Phi_2\gamma_2 + \gamma_3'\Phi_3\gamma_3\end{aligned}\tag{OA4}$$

Next, for terms concerning random effect variation, Johnson (2014) provides the general expression:

$$\overline{\sigma_l^2} = \text{tr}(\mathbf{Z}\mathbf{T}\mathbf{Z}') / N\tag{OA5}$$

with  $N$  denoting total sample size and  $\mathbf{Z}$  denoting a  $N \times (p_l + 1)$  design matrix for the random effects across level- $l$  units (i.e., a column of  $N$  1's for the level- $l$  intercept, and a column for each of the  $p_l$  predictors with a random slope varying across level- $l$ ) and  $\mathbf{T}$  denoting the random effect covariance matrix for level- $l$ . Using our notation, this can be computed for level-2 as

$$\begin{aligned}\overline{\sigma_{L2}^2} &= \text{tr}(\mathbf{Z}_{1*2}\mathbf{T}_{1*2}\mathbf{Z}'_{1*2}) / N \\ &= \text{tr}(\mathbf{T}_{1*2}\mathbf{Z}'_{1*2}\mathbf{Z}_{1*2}) / N \\ &= N \times \text{tr}(\mathbf{T}_{1*2} \frac{\mathbf{Z}'_{1*2}\mathbf{Z}_{1*2}}{N}) / N \\ &= \text{tr}(\mathbf{T}_{1*2} \frac{\mathbf{Z}'_{1*2}\mathbf{Z}_{1*2}}{N})\end{aligned}\tag{OA6}$$

Note that  $\frac{\mathbf{Z}'_{1*2}\mathbf{Z}_{1*2}}{N}$  denotes a  $(p_2 + 1) \times (p_2 + 1)$  matrix with the means of the squares of each element of  $\mathbf{Z}_{1*2}$  across all  $N$  observations on the diagonal, and the means of pairwise products of each nonredundant element of  $\mathbf{Z}_{1*2}$  across all  $N$  observations on the off-diagonals. We will call this matrix  $\overline{\mathbf{Z}_{1*2}^2}$ . Note also that, by the definition of variance,  $\Sigma_{1*2}$  (the covariance matrix of elements of  $\mathbf{w}'_{1*2ijk}$ ) can be given as  $\overline{\mathbf{Z}_{1*2}^2} - \overline{\mathbf{Z}_{1*2}}^2$ , with  $\overline{\mathbf{Z}_{1*2}}^2$  denoting a matrix with the squared means of each element of  $\mathbf{Z}_{1*2}$  across all  $N$  observations on the diagonal and the pairwise products of means of each nonredundant element of  $\mathbf{Z}_{1*2}$  across all  $N$  observations on the off-diagonals. Thus,

$$\begin{aligned}\overline{\sigma_{L2}^2} &= \text{tr}(\mathbf{T}_{1*2}\overline{\mathbf{Z}_{1*2}^2}) \\ &= \text{tr}(\mathbf{T}_{1*2}(\Sigma_{1*2} + \overline{\mathbf{Z}_{1*2}}^2)) \\ &= \text{tr}(\mathbf{T}_{1*2}\Sigma_{1*2} + \mathbf{T}_{1*2}\overline{\mathbf{Z}_{1*2}}^2) \\ &= \text{tr}(\mathbf{T}_{1*2}\Sigma_{1*2}) + \text{tr}(\mathbf{T}_{1*2}\overline{\mathbf{Z}_{1*2}}^2)\end{aligned}\tag{OA7}$$

With cluster-mean-centered level-1 predictors,  $\overline{\mathbf{Z}_{1*2}}$  contains the intercept variance as the first element and all other elements are 0. Thus,

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$$\begin{aligned}\overline{\sigma_{L2}^2} &= tr(\mathbf{T}_{1*2}\boldsymbol{\Sigma}_{1*2}) + tr(\mathbf{T}_{1*2}\overline{\mathbf{Z}}_{1*2}^2) \\ &= tr(\mathbf{T}_{1*2}\boldsymbol{\Sigma}_{1*2}) + \tau_{00}\end{aligned}\quad (\text{OA8})$$

For the random effects across level-3 units, we can express  $\overline{\sigma_l^2}$  as

$$\begin{aligned}\overline{\sigma_{L3}^2} &= tr\left(\begin{pmatrix} \mathbf{Z}_{1*3} & \mathbf{Z}_{2*3} \end{pmatrix} \begin{pmatrix} \mathbf{T}_{1*3} & \mathbf{0} \\ \mathbf{0} & \mathbf{T}_{2*3} \end{pmatrix} \begin{pmatrix} \mathbf{Z}'_{1*3} \\ \mathbf{Z}'_{2*3} \end{pmatrix}\right) / N \\ &= tr\left(\begin{pmatrix} \mathbf{Z}_{1*3}\mathbf{T}_{1*3} & \mathbf{Z}_{2*3}\mathbf{T}_{2*3} \end{pmatrix} \begin{pmatrix} \mathbf{Z}'_{1*3} \\ \mathbf{Z}'_{2*3} \end{pmatrix}\right) / N \\ &= tr(\mathbf{Z}_{1*3}\mathbf{T}_{1*3}\mathbf{Z}'_{1*3} + \mathbf{Z}_{2*3}\mathbf{T}_{2*3}\mathbf{Z}'_{2*3}) / N \\ &= (tr(\mathbf{Z}_{1*3}\mathbf{T}_{1*3}\mathbf{Z}'_{1*3}) + tr(\mathbf{Z}_{2*3}\mathbf{T}_{2*3}\mathbf{Z}'_{2*3})) / N \\ &= N \times \left( tr\left(\mathbf{T}_{1*3} \frac{\mathbf{Z}'_{1*3}\mathbf{Z}_{1*3}}{N}\right) + tr\left(\mathbf{T}_{2*3} \frac{\mathbf{Z}'_{2*3}\mathbf{Z}_{2*3}}{N}\right) \right) / N \\ &= tr\left(\mathbf{T}_{1*3} \frac{\mathbf{Z}'_{1*3}\mathbf{Z}_{1*3}}{N}\right) + tr\left(\mathbf{T}_{2*3} \frac{\mathbf{Z}'_{2*3}\mathbf{Z}_{2*3}}{N}\right)\end{aligned}\quad (\text{OA9})$$

Using the same steps and logic as shown above for  $\overline{\sigma_{L2}^2}$ ,

$$\begin{aligned}\overline{\sigma_{L3}^2} &= tr(\mathbf{T}_{1*3}\overline{\mathbf{Z}}_{1*3}^2) + tr(\mathbf{T}_{2*3}\overline{\mathbf{Z}}_{2*3}^2) \\ &= tr(\mathbf{T}_{1*3}\boldsymbol{\Sigma}_{1*3}) + tr(\mathbf{T}_{2*3}\boldsymbol{\Sigma}_{2*3}) + \varphi_{000}\end{aligned}\quad (\text{OA10})$$

Lastly,  $\sigma_\varepsilon^2$  is the same as our  $\sigma^2$ . Thus, we can express  $R_{NSJ(m)}^2$  as

$$\begin{aligned}R_{NSJ(m)}^2 &= \frac{\gamma'_1\boldsymbol{\Phi}_1\gamma_1 + \gamma'_2\boldsymbol{\Phi}_2\gamma_2 + \gamma'_3\boldsymbol{\Phi}_3\gamma_3}{\gamma'_1\boldsymbol{\Phi}_1\gamma_1 + \gamma'_2\boldsymbol{\Phi}_2\gamma_2 + \gamma'_3\boldsymbol{\Phi}_3\gamma_3 + tr(\boldsymbol{\Sigma}_{1*2}\mathbf{T}_{1*2}) + tr(\boldsymbol{\Sigma}_{1*3}\mathbf{T}_{1*3}) + tr(\boldsymbol{\Sigma}_{2*3}\mathbf{T}_{2*3}) + \varphi_{000} + \tau_{000} + \sigma^2} \\ &= R_t^{2(f_1)} + R_t^{2(f_2)} + R_t^{2(f_3)}\end{aligned}\quad (\text{OA11})$$

### Section A3: Correspondence with Johnson's (2014) extension of Nakagawa & Schielzeth's (2013) conditional measure

The linear mixed model version of Johnson's (2014) extension of Nakagawa & Schielzeth's (2013) conditional measure was defined in manuscript Equation (4) and is reproduced here:

$$R_{NSJ(c)}^2 = \frac{\sigma_f^2 + \overline{\sigma_{L2}^2} + \overline{\sigma_{L3}^2}}{\sigma_f^2 + \overline{\sigma_{L2}^2} + \overline{\sigma_{L3}^2} + \sigma_\varepsilon^2}\quad (\text{OA12})$$

Each of these terms was shown in Online Appendix Section A2 to be equivalent to certain terms from our variance partitioning. We can thus express  $R_{NSJ(c)}^2$  as

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$$\begin{aligned}
 R_{NSJ(c)}^2 &= \frac{\gamma_1' \Phi_1 \gamma_1 + \gamma_2' \Phi_2 \gamma_2 + \gamma_3' \Phi_3 \gamma_3 + tr(\Sigma_{1*2} \mathbf{T}_{1*2}) + tr(\Sigma_{1*3} \mathbf{T}_{1*3}) + tr(\Sigma_{2*3} \mathbf{T}_{2*3}) + \varphi_{000} + \tau_{000}}{\gamma_1' \Phi_1 \gamma_1 + \gamma_2' \Phi_2 \gamma_2 + \gamma_3' \Phi_3 \gamma_3 + tr(\Sigma_{1*2} \mathbf{T}_{1*2}) + tr(\Sigma_{1*3} \mathbf{T}_{1*3}) + tr(\Sigma_{2*3} \mathbf{T}_{2*3}) + \varphi_{000} + \tau_{000} + \sigma^2} \\
 &= R_t^{2(f_1)} + R_t^{2(f_2)} + R_t^{2(f_3)} + R_t^{2(v_{1*2})} + R_t^{2(v_{1*3})} + R_t^{2(v_{2*3})} + R_t^{2(m_2)} + R_t^{2(m_3)}
 \end{aligned}
 \tag{OA13}$$

**Section A4: Correspondence with Raudenbush & Bryk's (2002) level-1 measure**

Raudenbush & Bryk's (2002) (see also Bryk & Raudenbush, 1992) level-1 measure was defined in manuscript Equation (5) and is reproduced here:

$$R_{R\&B,1}^2 = \frac{\sigma_{(null)}^2 - \sigma^2}{\sigma_{(null)}^2} .
 \tag{OA14}$$

Here, the level-1 residual variance from a random-intercept-only model,  $\sigma_{(null)}^2$ , reflects the outcome variance at level-1. Replacing this term with our model-implied level-1 variance, this becomes

$$\begin{aligned}
 R_{R\&B,1}^{2*} &= \frac{(\gamma_1' \Phi_1 \gamma_1 + tr(\Sigma_{1*2} \mathbf{T}_{1*2}) + tr(\Sigma_{1*3} \mathbf{T}_{1*3}) + \sigma^2) - \sigma^2}{\gamma_1' \Phi_1 \gamma_1 + tr(\Sigma_{1*2} \mathbf{T}_{1*2}) + tr(\Sigma_{1*3} \mathbf{T}_{1*3}) + \sigma^2} \\
 &= \frac{\gamma_1' \Phi_1 \gamma_1 + tr(\Sigma_{1*2} \mathbf{T}_{1*2}) + tr(\Sigma_{1*3} \mathbf{T}_{1*3})}{\gamma_1' \Phi_1 \gamma_1 + tr(\Sigma_{1*2} \mathbf{T}_{1*2}) + tr(\Sigma_{1*3} \mathbf{T}_{1*3}) + \sigma^2} . \\
 &= R_1^{2(f_1)} + R_1^{2(v_{1*2})} + R_1^{2(v_{1*3})}
 \end{aligned}
 \tag{OA15}$$

**Section A5: Correspondence with Raudenbush & Bryk's (2002) level-2 measure**

Raudenbush & Bryk's (2002) (see also Bryk & Raudenbush, 1992) level-2 measure was defined in manuscript Equation (6) and is reproduced here:

$$R_{R\&B,2}^2 = \frac{\tau_{000(null)} - \tau_{000}}{\tau_{000(null)}}
 \tag{OA16}$$

Here, the level-2 residual variance from a random-intercept-only model,  $\tau_{000(null)}$ , reflects the outcome variance at level-2. Replacing this term with our model-implied level-2 variance, this becomes

$$\begin{aligned}
 R_{R\&B,2}^2 &= \frac{(\gamma_2' \Phi_2 \gamma_2 + tr(\Sigma_{2*3} \mathbf{T}_{2*3}) + \tau_{000}) - \tau_{000}}{\gamma_2' \Phi_2 \gamma_2 + tr(\Sigma_{2*3} \mathbf{T}_{2*3}) + \tau_{000}} \\
 &= \frac{\gamma_2' \Phi_2 \gamma_2 + tr(\Sigma_{2*3} \mathbf{T}_{2*3})}{\gamma_2' \Phi_2 \gamma_2 + tr(\Sigma_{2*3} \mathbf{T}_{2*3}) + \tau_{000}} \\
 &= R_2^{2(f_2)} + R_2^{2(v_2)}
 \end{aligned}
 \tag{OA17}$$

**Section A6: Correspondence with Raudenbush & Bryk’s (2002) level-3 measure**

Raudenbush & Bryk’s (2002) (see also Bryk & Raudenbush, 1992) level-3 measure was defined in manuscript Equation (7) and is reproduced here:

$$R_{R\&B,3}^2 = \frac{\varphi_{000(null)} - \varphi_{000}}{\varphi_{000(null)}} \tag{OA18}$$

Here, the level-3 residual variance from a random-intercept-only model,  $\varphi_{000(null)}$ , reflects the outcome variance at level-3. Replacing this term with our model-implied level-3 variance, this becomes

$$\begin{aligned} R_{R\&B,3}^{2*} &= \frac{(\boldsymbol{\gamma}'_3 \boldsymbol{\Phi}_3 \boldsymbol{\gamma}_3 + \varphi_{000}) - \varphi_{000}}{\boldsymbol{\gamma}'_3 \boldsymbol{\Phi}_3 \boldsymbol{\gamma}_3 + \varphi_{000}} \\ &= \frac{\boldsymbol{\gamma}'_3 \boldsymbol{\Phi}_3 \boldsymbol{\gamma}_3}{\boldsymbol{\gamma}'_3 \boldsymbol{\Phi}_3 \boldsymbol{\gamma}_3 + \varphi_{000}} \\ &= R_3^{2(f_3)} \end{aligned} \tag{OA19}$$

**Section A7: Correspondence with Singer & Willett’s (2003) and Peugh & Heck’s (2017) measure**

Singer & Willett’s (2003) measure (see also Peugh & Heck, 2017) was defined in manuscript Equation (8) and is reproduced here:

$$R_{S\&W}^2 = \text{corr}(\hat{y}_{ijk}^{(marg)}, y_{ijk})^2 \tag{OA20}$$

with  $\hat{y}_{ijk}^{(marg)}$  denoting a marginal predicted score for level-1 unit  $i$ , level-2 unit  $j$ , and level-3 unit  $k$ , i.e.,  $\hat{y}_{ijk}^{(marg)} = \gamma_{000} + \mathbf{x}'_{1ijk} \boldsymbol{\gamma}_1 + \mathbf{x}'_{2jk} \boldsymbol{\gamma}_2 + \mathbf{x}'_{3k} \boldsymbol{\gamma}_3$ . For simplicity, here we set  $\mathbf{x}' = (1 \quad \mathbf{x}'_{1ijk} \quad \mathbf{x}'_{2jk} \quad \mathbf{x}'_{3k})$  and  $\boldsymbol{\gamma}' = (\gamma_{000} \quad \boldsymbol{\gamma}'_1 \quad \boldsymbol{\gamma}'_2 \quad \boldsymbol{\gamma}'_3)$  so that  $\hat{y}_{ijk}^{(marg)} = \mathbf{x}' \boldsymbol{\gamma}$ .

We can re-express  $R_{S\&W}^2$  as

$$\begin{aligned} R_{S\&W}^2 &= \text{corr}(\hat{y}_{ijk}^{(marg)}, y_{ijk})^2 \\ &= \frac{\text{cov}(\hat{y}_{ijk}^{(marg)}, y_{ijk})^2}{\text{var}(\hat{y}_{ijk}^{(marg)}) \text{var}(y_{ijk})} \end{aligned} \tag{OA21}$$

Note that, in the population,

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$$\begin{aligned}
 \text{cov}(\hat{y}_{ijk}^{(marg)}, y_{ijk}) &= E[\hat{y}_{ijk}^{(marg)} y_{ijk}] - E[\hat{y}_{ijk}^{(marg)}]E[y_{ijk}] \\
 &= E[(\mathbf{x}'\boldsymbol{\gamma})(\mathbf{x}'\boldsymbol{\gamma} + \mathbf{w}'\mathbf{u} + e_{ijk})] - E[\mathbf{x}'\boldsymbol{\gamma}]E[\mathbf{x}'\boldsymbol{\gamma} + \mathbf{w}'\mathbf{u} + e_{ijk}] \\
 &= E[(\mathbf{x}'\boldsymbol{\gamma})^2 + (\mathbf{x}'\boldsymbol{\gamma})(\mathbf{w}'\mathbf{u}) + (\mathbf{x}'\boldsymbol{\gamma})e_{ijk}] - E[\mathbf{x}'\boldsymbol{\gamma}](E[\mathbf{x}'\boldsymbol{\gamma}] + E[\mathbf{w}'\mathbf{u}] + E[e_{ijk}]) \\
 &= E[(\mathbf{x}'\boldsymbol{\gamma})^2] + E[(\mathbf{x}'\boldsymbol{\gamma})(\mathbf{w}'\mathbf{u})] + E[(\mathbf{x}'\boldsymbol{\gamma})e_{ijk}] - E[\mathbf{x}'\boldsymbol{\gamma}]E[\mathbf{x}'\boldsymbol{\gamma}] \\
 &= E[(\mathbf{x}'\boldsymbol{\gamma})^2] + E[(\mathbf{x}'\boldsymbol{\gamma})]E[(\mathbf{w}'\mathbf{u})] + E[(\mathbf{x}'\boldsymbol{\gamma})]E[e_{ijk}] - E[\mathbf{x}'\boldsymbol{\gamma}]^2 \\
 &= E[(\mathbf{x}'\boldsymbol{\gamma})^2] - E[\mathbf{x}'\boldsymbol{\gamma}]^2 \\
 &= \text{var}(\hat{y}_{ijk}^{(marg)})
 \end{aligned}
 \tag{OA22}$$

Thus,

$$\begin{aligned}
 R_{S\&W}^{2*} &= \frac{\text{cov}(\hat{y}_{ijk}^{(marg)}, y_{ijk})^2}{\text{var}(\hat{y}_{ijk}^{(marg)}) \text{var}(y_{ijk})} \\
 &= \frac{\text{var}(\hat{y}_{ijk}^{(marg)})^2}{\text{var}(\hat{y}_{ijk}^{(marg)}) \text{var}(y_{ijk})} \\
 &= \frac{\text{var}(\hat{y}_{ijk}^{(marg)})}{\text{var}(y_{ijk})}
 \end{aligned}
 \tag{OA23}$$

Using our model-implied variances, per the derivation in manuscript Appendix A this becomes

$$\begin{aligned}
 R_{S\&W}^{2*} &= \frac{\text{var}(\mathbf{x}'\boldsymbol{\gamma})}{\text{var}(\mathbf{x}'\boldsymbol{\gamma} + \mathbf{w}'\mathbf{u} + e_{ijk})} \\
 &= \frac{\boldsymbol{\gamma}'_1 \boldsymbol{\Phi}_1 \boldsymbol{\gamma}_1 + \boldsymbol{\gamma}'_2 \boldsymbol{\Phi}_2 \boldsymbol{\gamma}_2 + \boldsymbol{\gamma}'_3 \boldsymbol{\Phi}_3 \boldsymbol{\gamma}_3}{\boldsymbol{\gamma}'_1 \boldsymbol{\Phi}_1 \boldsymbol{\gamma}_1 + \boldsymbol{\gamma}'_2 \boldsymbol{\Phi}_2 \boldsymbol{\gamma}_2 + \boldsymbol{\gamma}'_3 \boldsymbol{\Phi}_3 \boldsymbol{\gamma}_3 + \text{tr}(\boldsymbol{\Sigma}_{1*2} \mathbf{T}_{1*2}) + \text{tr}(\boldsymbol{\Sigma}_{1*3} \mathbf{T}_{1*3}) + \text{tr}(\boldsymbol{\Sigma}_{2*3} \mathbf{T}_{2*3}) + \varphi_{000} + \tau_{000} + \sigma^2} \\
 &= R_t^{2(f_1)} + R_t^{2(f_2)} + R_t^{2(f_3)}
 \end{aligned}
 \tag{OA24}$$

**Online Appendix B: Derivation of analytic relationships between total and level-specific  $R^2$  measures**

In this online appendix, we formally derive the relationship between total and level-specific measures that have the same source of explained variance (denoted generically as  $s$ ). We show that they have a conditionally linear, positive relationship that is *moderated* by the amount of cluster dependency, i.e., the proportion of total variance that is across clusters, or intraclass correlation [ICC]. Preliminarily, we note that the proportion of total variance that is across both level-2 and level-3 units, or  $ICC_{23}$ , can be computed with our variance decomposition as:

$$\begin{aligned}
 ICC_{23} &= \frac{\text{level-2 variance} + \text{level-3 variance}}{\text{total variance}} \\
 &= \frac{\gamma'_2 \Phi_2 \gamma_2 + \gamma'_3 \Phi_3 \gamma_3 + tr(\Sigma_{2*3} \mathbf{T}_{2*3}) + \varphi_{000} + \tau_{000}}{\gamma'_1 \Phi_1 \gamma_1 + \gamma'_2 \Phi_2 \gamma_2 + \gamma'_3 \Phi_3 \gamma_3 + tr(\Sigma_{1*2} \mathbf{T}_{1*2}) + tr(\Sigma_{1*3} \mathbf{T}_{1*3}) + tr(\Sigma_{2*3} \mathbf{T}_{2*3}) + \varphi_{000} + \tau_{000} + \sigma^2}
 \end{aligned}
 \tag{OB1}$$

The proportion of total variance that is specifically at level-2 is

$$\begin{aligned}
 ICC_2 &= \frac{\text{level-2 variance}}{\text{total variance}} \\
 &= \frac{\gamma'_2 \Phi_2 \gamma_2 + tr(\Sigma_{2*3} \mathbf{T}_{2*3}) + \tau_{000}}{\gamma'_1 \Phi_1 \gamma_1 + \gamma'_2 \Phi_2 \gamma_2 + \gamma'_3 \Phi_3 \gamma_3 + tr(\Sigma_{1*2} \mathbf{T}_{1*2}) + tr(\Sigma_{1*3} \mathbf{T}_{1*3}) + tr(\Sigma_{2*3} \mathbf{T}_{2*3}) + \varphi_{000} + \tau_{000} + \sigma^2}
 \end{aligned}
 \tag{OB2}$$

And the proportion of total variance that is at level-3 is

$$\begin{aligned}
 ICC_3 &= \frac{\text{level-3 variance}}{\text{total variance}} \\
 &= \frac{\gamma'_3 \Phi_3 \gamma_3 + \varphi_{000}}{\gamma'_1 \Phi_1 \gamma_1 + \gamma'_2 \Phi_2 \gamma_2 + \gamma'_3 \Phi_3 \gamma_3 + tr(\Sigma_{1*2} \mathbf{T}_{1*2}) + tr(\Sigma_{1*3} \mathbf{T}_{1*3}) + tr(\Sigma_{2*3} \mathbf{T}_{2*3}) + \varphi_{000} + \tau_{000} + \sigma^2}
 \end{aligned}
 \tag{OB3}$$

A level-1 measure,  $R_1^{2(s)}$ , and a total measure,  $R_t^{2(s)}$ , are related purely through the degree of higher level clustering, or  $ICC_{23}$ :

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$$\begin{aligned}
 R_1^{2(s)} &= \frac{\theta_s}{\gamma_1' \Phi_1 \gamma_1 + tr(\Sigma_{1*2} \mathbf{T}_{1*2}) + tr(\Sigma_{1*3} \mathbf{T}_{1*3}) + \sigma^2} \\
 &= \frac{\theta_s / \text{var}(y_{ijk})}{(\gamma_1' \Phi_1 \gamma_1 + tr(\Sigma_{1*2} \mathbf{T}_{1*2}) + tr(\Sigma_{1*3} \mathbf{T}_{1*3}) + \sigma^2) / \text{var}(y_{ijk})} \\
 &= \frac{R_t^{2(s)}}{(\gamma_1' \Phi_1 \gamma_1 + tr(\Sigma_{1*2} \mathbf{T}_{1*2}) + tr(\Sigma_{1*3} \mathbf{T}_{1*3}) + \sigma^2) / \text{var}(y_{ijk})} \\
 &= \frac{R_t^{2(s)}}{(\text{var}(y_{ijk}) - (\gamma_2' \Phi_2 \gamma_2 + \gamma_3' \Phi_3 \gamma_3 + tr(\Sigma_{2*3} \mathbf{T}_{2*3}) + \varphi_{000} + \tau_{000})) / \text{var}(y_{ijk})} \\
 &= \frac{R_t^{2(s)}}{\text{var}(y_{ijk}) / \text{var}(y_{ijk}) - (\gamma_2' \Phi_2 \gamma_2 + \gamma_3' \Phi_3 \gamma_3 + tr(\Sigma_{2*3} \mathbf{T}_{2*3}) + \varphi_{000} + \tau_{000}) / \text{var}(y_{ijk})} \\
 &= \frac{R_t^{2(s)}}{1 - ICC_{23}}
 \end{aligned} \tag{OB4}$$

A level-2 measure,  $R_2^{2(s)}$ , and a total measure,  $R_t^{2(s)}$ , are related purely through the degree of clustering at level-2, or  $ICC_2$ :

$$\begin{aligned}
 R_2^{2(s)} &= \frac{\theta_s}{\gamma_2' \Phi_2 \gamma_2 + tr(\Sigma_{2*3} \mathbf{T}_{2*3}) + \tau_{000}} \\
 &= \frac{\theta_s / \text{var}(y_{ijk})}{(\gamma_2' \Phi_2 \gamma_2 + tr(\Sigma_{2*3} \mathbf{T}_{2*3}) + \tau_{000}) / \text{var}(y_{ijk})} \\
 &= \frac{R_t^{2(s)}}{ICC_2}
 \end{aligned} \tag{OB5}$$

A level-3 measure,  $R_3^{2(s)}$ , and a total measure,  $R_t^{2(s)}$ , are related purely through the degree of clustering at level-3, or  $ICC_3$ :

$$\begin{aligned}
 R_3^{2(s)} &= \frac{\theta_s}{\gamma_3' \Phi_3 \gamma_3 + \varphi_{000}} \\
 &= \frac{\theta_s / \text{var}(y_{ijk})}{(\gamma_3' \Phi_3 \gamma_3 + \varphi_{000}) / \text{var}(y_{ijk})} \\
 &= \frac{R_t^{2(s)}}{ICC_3}
 \end{aligned} \tag{OB6}$$



**Online Appendix C: Derivation showing that R-squared measures obtained from a cluster-mean-centered model and those obtained from a model that instead centers predictors by a constant value will be equivalent when predictors have variance at only one level**

Here we compare the full set of total and level-specific R-squared measures obtained from a cluster-mean-centered model (using the formulas described in manuscript Table 1) to the full set of total and level-specific R-squared measures obtained from a model in which predictors are instead centered by an arbitrary constant (using the formulas described in manuscript Table 5). In particular, we show that, when each raw predictor has variance at only one level, the full set of R-squared measures will be the same whether predictors are centered by cluster means (which, in this case, would be equivalent to the grand means) or by any other arbitrary constant. The general idea is that centering predictors by a constant will always yield a likelihood-equivalent model, and as such, the model-implied total and level-specific variances will not change, nor will the proportion of variance attributable to each individual source.

We start with a three-level model in which we predict the outcome,  $y_{ijk}$  (with  $i$  denoting observation within-cluster,  $j$  denoting level-2 cluster within level-3 cluster, and  $k$  denoting level-3 cluster) with a level-1 predictor  $x_{ijk}$ , a level-2 predictor  $w_{jk}$ , and a level-3 predictor  $z_k$ .

$$y_{ijk} = \gamma_0 + \gamma_1 x_{ijk} + \gamma_2 w_{jk} + \gamma_3 z_k + u_{0jk} + u_{0k} + u_{1jk} x_{ijk} + u_{1k} x_{ijk} + u_{2k} w_{jk} + e_{ijk}$$

$$e_{ijk} \sim N(0, \sigma^2) \tag{OC1}$$

$$\begin{bmatrix} u_{0jk} \\ u_{1jk} \\ u_{0k} \\ u_{1k} \\ u_{2k} \end{bmatrix} \sim MVN \left( \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \tau_{00*2} & & & & \\ \tau_{01*2} & \tau_{11*2} & & & \\ 0 & 0 & \tau_{00*3} & & \\ 0 & 0 & \tau_{01*3} & \tau_{11*3} & \\ 0 & 0 & \tau_{02*3} & \tau_{12*3} & \tau_{22*3} \end{bmatrix} \right)$$

As shown in Equation OC1, the model contains a random intercept that varies across level-2 and level-3 units, a random slope of  $x_{ijk}$  that varies across level-2 and level-3 units, a random slope of  $w_{jk}$  that varies across level-3 units, and a fixed slope of  $z_k$ . Here we will assume that each predictor has variance exclusively at its respective level, and each is centered such that it has a mean of 0. Thus, we will term this model in Equation OC1 the *mean-centered model* (noting that  $x_{ijk}$  and  $w_{jk}$  can be considered to be either grand-mean-centered or cluster-mean-centered, as these two centering options are equivalent in this context). For this model, we can thus use the formulas in manuscript Equations 10-18 (for cluster-mean-centered models) to compute the total variance attributable to each source.

The total variance attributable to source  $f_1$  in the *mean-centered model* is given as

$$\begin{aligned} \gamma_1' \Phi \gamma_1 &= [\gamma_{100}] [\text{var}(x_{ijk})] [\gamma_{100}] \\ &= \gamma_{100}^2 \text{var}(x_{ijk}) \end{aligned} \tag{OC2}$$

The total variance attributable to source  $v_{1*2}$  is

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$$\begin{aligned}
 tr(\Sigma_{1*2} \mathbf{T}_{1*2}) &= tr \left( \begin{bmatrix} 0 & \\ 0 & \text{var}(x_{ijk}) \end{bmatrix} \begin{bmatrix} \tau_{00*2} & \\ \tau_{01*2} & \tau_{11*2} \end{bmatrix} \right) \\
 &= tr \left( \begin{bmatrix} 0 & 0 \\ 0 & \text{var}(x_{ijk}) \tau_{11*2} \end{bmatrix} \right) \\
 &= \text{var}(x_{ijk}) \tau_{11*2}
 \end{aligned} \tag{OC3}$$

The total variance attributable to source  $v_{1*3}$  is

$$\begin{aligned}
 tr(\Sigma_{1*3} \mathbf{T}_{1*3}) &= tr \left( \begin{bmatrix} 0 & \\ 0 & \text{var}(x_{ijk}) \end{bmatrix} \begin{bmatrix} \tau_{00*3} & \\ \tau_{01*3} & \tau_{11*3} \end{bmatrix} \right) \\
 &= tr \left( \begin{bmatrix} 0 & 0 \\ 0 & \text{var}(x_{ijk}) \tau_{11*3} \end{bmatrix} \right) \\
 &= \text{var}(x_{ijk}) \tau_{11*3}
 \end{aligned} \tag{OC4}$$

The total variance attributable to source  $v_{2*3}$  is

$$\begin{aligned}
 tr(\Sigma_{2*3} \mathbf{T}_{2*3}) &= tr \left( \begin{bmatrix} \text{var}(w_{jk}) \end{bmatrix} \begin{bmatrix} \tau_{22*3} \end{bmatrix} \right) \\
 &= tr \left( \begin{bmatrix} \text{var}(w_{jk}) \tau_{22*3} \end{bmatrix} \right) \\
 &= \text{var}(w_{jk}) \tau_{22*3}
 \end{aligned} \tag{OC5}$$

And the total variance attributable to source  $m_2$  is given simply as  $\tau_{00*2}$ , to source  $m_3$  as  $\tau_{00*3}$ , and to level-1 residuals as  $\sigma^2$  (note that we are using modified notation for the variance components, for instance, in that  $\varphi_{000}$  in manuscript equation 17 is listed as  $\tau_{00*3}$  here in Online Appendix C; this is simply to facilitate a direct comparison between parameters from the *mean-centered model* to the later-defined model with alternative centering).

Adding each of these individual variances together yields the following the model-implied total variance for the *mean-centered model*:

$$\begin{aligned}
 \text{var}(y_{ijk}) &= \gamma_1^2 \text{var}(x_{ijk}) + \gamma_2^2 \text{var}(w_{jk}) + \gamma_3^2 \text{var}(z_k) \\
 &\quad + \tau_{11*2} \text{var}(x_{ijk}) + \tau_{11*3} \text{var}(x_{ijk}) + \tau_{22*3} \text{var}(w_{jk}) + \tau_{00*2} + \tau_{00*3} + \sigma^2
 \end{aligned} \tag{OC6}$$

Adding the level-1 variances yields the model-implied level-1 outcome variance:

$$\text{var}_{ijk}(y_{ijk}) = \gamma_1^2 \text{var}(x_{ijk}) + \tau_{11*2} \text{var}(x_{ijk}) + \tau_{11*3} \text{var}(x_{ijk}) + \sigma^2 \tag{OC7}$$

Adding the level-2 variances yields the model-implied level-2 outcome variance:

$$\text{var}(y_{jk}) = \gamma_2^2 \text{var}(w_{jk}) + \tau_{22*3} \text{var}(w_{jk}) + \tau_{00*2} \tag{OC8}$$

And adding the level-3 variances yields the model-implied level-3 outcome variance:

$$\text{var}_k(y_{ijk}) = \gamma_3^2 \text{var}(z_k) + \tau_{00*3} \tag{OC9}$$

We can thus form the following total R-squared measures for the *mean-centered model* as such, using the formulas provided for cluster-mean-centered models in Table 1:

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$$R_t^{2(f_1)} = \frac{\gamma_1^2 \text{var}(x_{ijk})}{\text{Eqn OC6}}$$

$$R_t^{2(f_2)} = \frac{\gamma_2^2 \text{var}(w_{jk})}{\text{Eqn OC6}}$$

$$R_t^{2(f_3)} = \frac{\gamma_3^2 \text{var}(z_k)}{\text{Eqn OC6}}$$

$$R_t^{2(v_{1*2})} = \frac{\tau_{11*2} \text{var}(x_{ijk})}{\text{Eqn OC6}}$$

$$R_t^{2(v_{1*3})} = \frac{\tau_{11*3} \text{var}(x_{ijk})}{\text{Eqn OC6}}$$

$$R_t^{2(v_{2*3})} = \frac{\tau_{22*3} \text{var}(w_{jk})}{\text{Eqn OC6}}$$

$$R_t^{2(m_2)} = \frac{\tau_{00*2}}{\text{Eqn OC6}}$$

$$R_t^{2(m_3)} = \frac{\tau_{00*3}}{\text{Eqn OC6}} \tag{OC10}$$

As well as the following level-specific measures:

$$R_1^{2(f_1)} = \frac{\gamma_1^2 \text{var}(x_{ijk})}{\text{Eqn OC7}}$$

$$R_2^{2(f_2)} = \frac{\gamma_2^2 \text{var}(w_{jk})}{\text{Eqn OC8}}$$

$$R_3^{2(f_3)} = \frac{\gamma_3^2 \text{var}(z_k)}{\text{Eqn OC9}}$$

$$R_1^{2(v_{1*2})} = \frac{\tau_{11*2} \text{var}(x_{ijk})}{\text{Eqn OC7}}$$

$$R_1^{2(v_{1*3})} = \frac{\tau_{11*3} \text{var}(x_{ijk})}{\text{Eqn OC7}}$$

$$R_2^{2(v_{2*3})} = \frac{\tau_{22*3} \text{var}(w_{jk})}{\text{Eqn OC8}}$$

$$R_2^{2(m_2)} = \frac{\tau_{00*2}}{\text{Eqn OC8}}$$

$$R_3^{2(m_3)} = \frac{\tau_{00*3}}{\text{Eqn OC9}} \tag{OC11}$$

We will next consider an alternative model specification wherein we center  $x_{ijk}$ ,  $w_{jk}$ , and  $z_k$  each by their own arbitrary constant ( $a$ ,  $b$ , and  $c$ , respectively).

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$$y_{ijk} = \gamma_0^* + \gamma_1^*(x_{ijk} - a) + \gamma_2^*(w_{jk} - b) + \gamma_3^*(z_k - c) + u_{0jk}^* + u_{0k}^* + u_{1jk}^*(x_{ijk} - a) + u_{1k}^*(x_{ijk} - a) + u_{2k}^*(w_{jk} - b) + e_{ijk}^* \quad (\text{OC12})$$

Here we use asterisks to distinguish the parameters from this *centered-by-constant model* to those from the *mean-centered model*. Because these are likelihood-equivalent models, however, they are simply reparameterizations of each other. As such, we can re-express the *centered-by-constant model* in the same form of the *mean-centered model* (i.e., as regression of y on x, w, and z) to establish equivalencies between the model expressions (following similar procedures to that in Kreft, de Leeuw, & Aiken [1995] and Brincks et al. [2017]).

$$y_{ijk} = (\gamma_0^* - \gamma_1^*a - \gamma_2^*b - \gamma_3^*c) + \gamma_1^*x_{ijk} + \gamma_2^*w_{jk} + \gamma_3^*z_k + (u_{0jk}^* - u_{1jk}^*a) + (u_{0k}^* - u_{1k}^*a - u_{2k}^*b) + u_{1jk}^*x_{ijk} + u_{1k}^*x_{ijk} + u_{2k}^*w_{jk} + e_{ijk}^* \quad (\text{OC13})$$

This re-expression reveals the following equalities between the *centered-by-constant model* and the *mean-centered model*:

$$\begin{aligned} \gamma_0 &= \gamma_0^* - \gamma_1^*a - \gamma_2^*b - \gamma_3^*c \\ \gamma_1 &= \gamma_1^* \\ \gamma_2 &= \gamma_2^* \\ \gamma_3 &= \gamma_3^* \\ u_{0jk} &= u_{0jk}^* - u_{1jk}^*a \\ u_{0k} &= u_{0k}^* - u_{1k}^*a - u_{2k}^*b \\ u_{1jk} &= u_{1jk}^* \\ u_{1k} &= u_{1k}^* \\ u_{2k} &= u_{2k}^* \\ e_{ijk} &= e_{ijk}^* \end{aligned} \quad (\text{OC14})$$

These further imply the following:

$$\begin{aligned} \gamma_0^* &= \gamma_0 + \gamma_1 a + \gamma_2 b + \gamma_3 c \\ \gamma_1^* &= \gamma_1 \\ \gamma_2^* &= \gamma_2 \\ \gamma_3^* &= \gamma_3 \\ u_{0jk}^* &= u_{0jk} + u_{1jk} a \\ u_{0k}^* &= u_{0k} + u_{1k} a + u_{2k} b \\ u_{1jk}^* &= u_{1jk} \\ u_{1k}^* &= u_{1k} \\ u_{2k}^* &= u_{2k} \\ e_{ijk}^* &= e_{ijk} \end{aligned} \quad (\text{OC15})$$

Using the equivalencies established in Equation OC15, we can rewrite the *centered-by-constant model* (with a regression of y on x - a, w - b, and z - c) as



$$\begin{aligned}
 \Phi_3 &= \begin{bmatrix} 0 & & & \\ 0 & \text{var}(x_{..k} - a) & & \\ 0 & 0 & \text{var}(w_{.k} - a) & \\ 0 & 0 & 0 & \text{var}(z_k - a) \end{bmatrix} \\
 &= \begin{bmatrix} 0 & & & \\ 0 & \text{var}(x_{..k}) & & \\ 0 & 0 & \text{var}(w_{.k}) & \\ 0 & 0 & 0 & \text{var}(z_k) \end{bmatrix} \tag{OC20} \\
 &= \begin{bmatrix} 0 & & & \\ 0 & 0 & & \\ 0 & 0 & 0 & \\ 0 & 0 & 0 & \text{var}(z_k) \end{bmatrix}
 \end{aligned}$$

The  $\Sigma$  matrices are then

$$\begin{aligned}
 \Sigma_{1*2} &= \begin{bmatrix} 0 & \\ 0 & \text{var}((x_{ijk} - a) - (x_{.jk} - a)) \end{bmatrix} \\
 &= \begin{bmatrix} 0 & \\ 0 & \text{var}(x_{ijk}) \end{bmatrix} \tag{OC21}
 \end{aligned}$$

$$\begin{aligned}
 \Sigma_{2*2} &= \begin{bmatrix} 0 & \\ 0 & \text{var}((x_{.jk} - a) - (x_{..k} - a)) \end{bmatrix} \\
 &= \begin{bmatrix} 0 & \\ 0 & 0 \end{bmatrix} \tag{OC22}
 \end{aligned}$$

$$\begin{aligned}
 \Sigma_{3*2} &= \begin{bmatrix} 0 & \\ 0 & \text{var}(x_{..k} - a) \end{bmatrix} \\
 &= \begin{bmatrix} 0 & \\ 0 & 0 \end{bmatrix} \tag{OC23}
 \end{aligned}$$

$$\begin{aligned}
 \Sigma_{1*3} &= \begin{bmatrix} 0 & & \\ 0 & \text{var}((x_{ijk} - a) - (x_{.jk} - a)) & \\ 0 & 0 & \text{var}((w_{jk} - b) - (w_{.k} - b)) \end{bmatrix} \\
 &= \begin{bmatrix} 0 & & \\ 0 & \text{var}(x_{ijk}) & \\ 0 & 0 & 0 \end{bmatrix} \tag{OC24}
 \end{aligned}$$

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$$\Sigma_{2*3} = \begin{bmatrix} 0 & & \\ 0 & \text{var}((x_{.jk} - a) - (x_{..k} - a)) & \\ 0 & 0 & \text{var}((w_{jk} - b) - (w_{.k} - b)) \end{bmatrix} \quad (\text{OC25})$$

$$= \begin{bmatrix} 0 & & \\ 0 & 0 & \\ 0 & 0 & \text{var}(w_{jk}) \end{bmatrix}$$

$$\Sigma_{3*3} = \begin{bmatrix} 0 & & \\ 0 & \text{var}(x_{..k} - a) & \\ 0 & 0 & \text{var}(w_{.k} - a) \end{bmatrix} \quad (\text{OC26})$$

$$= \begin{bmatrix} 0 & & \\ 0 & \text{var}(x_{..k}) & \\ 0 & 0 & \text{var}(w_{.k}) \end{bmatrix}$$

$$= \begin{bmatrix} 0 & & \\ 0 & 0 & \\ 0 & 0 & 0 \end{bmatrix}$$

The **T** matrices are

$$\mathbf{T}_2 = \begin{bmatrix} \text{var}(u_{0jk} + u_{1jk}a) & \\ \text{cov}(u_{0jk} + u_{1jk}a, u_{1jk}) & \text{var}(u_{1jk}) \end{bmatrix} \quad (\text{OC27})$$

$$= \begin{bmatrix} \text{var}(u_{0jk}) + a^2 \text{var}(u_{1jk}) + 2a \text{cov}(u_{0jk}, u_{1jk}) & \\ \text{cov}(u_{0jk}, u_{1jk}) + a \text{cov}(u_{1jk}, u_{1jk}) & \text{var}(u_{1jk}) \end{bmatrix}$$

$$= \begin{bmatrix} \tau_{00*2} + a^2 \tau_{11*2} + 2a\tau_{01*2} & \\ \tau_{01*2} + a\tau_{11*2} & \tau_{11*2} \end{bmatrix}$$

$$\mathbf{T}_3 = \begin{bmatrix} \text{var}(u_{0k} + u_{1k}a + u_{2k}b) & & \\ \text{cov}(u_{0k} + u_{1k}a + u_{2k}b, u_{1k}) & \text{var}(u_{1k}) & \\ \text{cov}(u_{0k} + u_{1k}a + u_{2k}b, u_{2k}) & \text{cov}(u_{1k}, u_{2k}) & \text{var}(u_{2k}) \end{bmatrix} \quad (\text{OC28})$$

$$= \begin{bmatrix} \text{var}(u_{0k}) + a^2 \text{var}(u_{1k}) + b^2 \text{var}(u_{2k}) + 2a \text{cov}(u_{0k}, u_{1k}) + 2b \text{cov}(u_{0k}, u_{2k}) + 2ab \text{cov}(u_{1k}, u_{2k}) & & \\ \text{cov}(u_{0k}, u_{1k}) + a \text{cov}(u_{1k}, u_{1k}) + b \text{cov}(u_{2k}, u_{1k}) & \text{var}(u_{1k}) & \\ \text{cov}(u_{0k}, u_{2k}) + a \text{cov}(u_{1k}, u_{2k}) + b \text{cov}(u_{2k}, u_{2k}) & \text{cov}(u_{1k}, u_{2k}) & \text{var}(u_{2k}) \end{bmatrix}$$

$$= \begin{bmatrix} \tau_{00*3} + a^2 \tau_{11*3} + b^2 \tau_{22*3} + 2a\tau_{01*3} + 2b\tau_{02*3} + 2ab\tau_{12*3} & & \\ \tau_{01*3} + a\tau_{11*3} + b\tau_{12*3} & \tau_{11*3} & \\ \tau_{02*3} + a\tau_{12*3} + b\tau_{22*3} & \tau_{12*3} & \tau_{22*3} \end{bmatrix}$$

And the **m** vectors are

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$$\begin{aligned}
 \mathbf{m}_{1*2} &= \begin{bmatrix} 1-1 \\ E[(x_{ijk} - a) - (x_{.jk} - a)] \end{bmatrix} \\
 &= \begin{bmatrix} 0 \\ E[x_{ijk} - x_{.jk}] \end{bmatrix} \\
 &= \begin{bmatrix} 0 \\ E[x_{ijk}] - E[x_{.jk}] \end{bmatrix} \\
 &= \begin{bmatrix} 0 \\ 0 \end{bmatrix}
 \end{aligned}
 \tag{OC29}$$

$$\begin{aligned}
 \mathbf{m}_{2*2} &= \begin{bmatrix} 1-1 \\ E[(x_{.jk} - a) - (x_{..k} - a)] \end{bmatrix} \\
 &= \begin{bmatrix} 0 \\ E[x_{.jk} - x_{..k}] \end{bmatrix} \\
 &= \begin{bmatrix} 0 \\ E[x_{.jk}] - E[x_{..k}] \end{bmatrix} \\
 &= \begin{bmatrix} 0 \\ 0 \end{bmatrix}
 \end{aligned}
 \tag{OC30}$$

$$\begin{aligned}
 \mathbf{m}_{3*2} &= \begin{bmatrix} 1 \\ E[x_{..k} - a] \end{bmatrix} \\
 &= \begin{bmatrix} 1 \\ E[x_{..k}] - a \end{bmatrix} \\
 &= \begin{bmatrix} 1 \\ -a \end{bmatrix}
 \end{aligned}
 \tag{OC31}$$

$$\begin{aligned}
 \mathbf{m}_{1*3} &= \begin{bmatrix} 1-1 \\ E[(x_{ijk} - a) - (x_{.jk} - a)] \\ E[(w_{jk} - b) - (w_{jk} - b)] \end{bmatrix} \\
 &= \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}
 \end{aligned}
 \tag{OC32}$$



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$$\begin{aligned}
 \mathbf{m}_{2*3} &= \begin{bmatrix} 1-1 \\ E[(x_{.jk} - a) - (x_{..k} - a)] \\ E[(w_{jk} - b) - (w_{.k} - b)] \end{bmatrix} \\
 &= \begin{bmatrix} 0 \\ E[x_{.jk} - x_{..k}] \\ E[w_{jk} - w_{.k}] \end{bmatrix} \\
 &= \begin{bmatrix} 0 \\ E[x_{.jk}] - E[x_{..k}] \\ E[w_{jk}] - E[w_{.k}] \end{bmatrix} \\
 &= \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}
 \end{aligned} \tag{OC33}$$

$$\begin{aligned}
 \mathbf{m}_{3*3} &= \begin{bmatrix} 1 \\ E[x_{..k} - a] \\ E[w_{.k} - b] \end{bmatrix} \\
 &= \begin{bmatrix} 1 \\ E[x_{..k}] - a \\ E[w_{.k}] - b \end{bmatrix} \\
 &= \begin{bmatrix} 1 \\ -a \\ -b \end{bmatrix}
 \end{aligned} \tag{OC34}$$

Using these matrices, the total variance attributable to source  $f_1$  in the *centered-by-constant model* is thus given as

$$\begin{aligned}
 \boldsymbol{\gamma}'\boldsymbol{\Phi}_1\boldsymbol{\gamma} &= \begin{bmatrix} \gamma_0 + \gamma_1 a + \gamma_2 b + \gamma_3 c & \gamma_1 & \gamma_2 & \gamma_3 \end{bmatrix} \begin{bmatrix} 0 & & & \\ 0 & \text{var}(x_{ijk}) & & \\ 0 & 0 & 0 & \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \gamma_0 + \gamma_1 a + \gamma_2 b + \gamma_3 c \\ \gamma_1 \\ \gamma_2 \\ \gamma_3 \end{bmatrix} \\
 &= \begin{bmatrix} 0 & \gamma_1 & \text{var}(x_{ijk}) & 0 & 0 \end{bmatrix} \begin{bmatrix} \gamma_0 + \gamma_1 a + \gamma_2 b + \gamma_3 c \\ \gamma_1 \\ \gamma_2 \\ \gamma_3 \end{bmatrix} \\
 &= \gamma_1^2 \text{var}(x_{ijk})
 \end{aligned} \tag{OC35}$$

The total variance attributable to  $f_2$  is

$$\begin{aligned}
 \boldsymbol{\gamma}'\boldsymbol{\Phi}_2\boldsymbol{\gamma} &= \begin{bmatrix} \gamma_0 + \gamma_1 a + \gamma_2 b + \gamma_3 c & \gamma_1 & \gamma_2 & \gamma_3 \end{bmatrix} \begin{bmatrix} 0 & & & \\ 0 & 0 & & \\ 0 & 0 & \text{var}(w_{jk}) & \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \gamma_0 + \gamma_1 a + \gamma_2 b + \gamma_3 c \\ \gamma_1 \\ \gamma_2 \\ \gamma_3 \end{bmatrix} \\
 &= \begin{bmatrix} 0 & 0 & \gamma_2 \text{var}(w_{jk}) & 0 \end{bmatrix} \begin{bmatrix} \gamma_0 + \gamma_1 a + \gamma_2 b + \gamma_3 c \\ \gamma_1 \\ \gamma_2 \\ \gamma_3 \end{bmatrix} \\
 &= \gamma_2^2 \text{var}(w_{jk})
 \end{aligned}$$

(OC36)

The total variance attributable to  $f_3$  is

$$\begin{aligned}
 \boldsymbol{\gamma}'\boldsymbol{\Phi}_3\boldsymbol{\gamma} &= \begin{bmatrix} \gamma_0 + \gamma_1 a + \gamma_2 b + \gamma_3 c & \gamma_1 & \gamma_2 & \gamma_3 \end{bmatrix} \begin{bmatrix} 0 & & & \\ 0 & 0 & & \\ 0 & 0 & 0 & \\ 0 & 0 & 0 & \text{var}(z_j) \end{bmatrix} \begin{bmatrix} \gamma_0 + \gamma_1 a + \gamma_2 b + \gamma_3 c \\ \gamma_1 \\ \gamma_2 \\ \gamma_3 \end{bmatrix} \\
 &= \begin{bmatrix} 0 & 0 & 0 & \gamma_3 \text{var}(z_j) \end{bmatrix} \begin{bmatrix} \gamma_0 + \gamma_1 a + \gamma_2 b + \gamma_3 c \\ \gamma_1 \\ \gamma_2 \\ \gamma_3 \end{bmatrix} \\
 &= \gamma_3^2 \text{var}(z_j)
 \end{aligned}$$

(OC37)

The total variance attributable to  $v_{1*2}$  is

$$\begin{aligned}
 \text{tr}(\boldsymbol{\Sigma}_{1*2} \mathbf{T}_2) &= \text{tr} \left( \begin{bmatrix} 0 & \\ 0 & \text{var}(x_{ijk}) \end{bmatrix} \begin{bmatrix} \tau_{00*2} + a^2\tau_{11*2} + 2a\tau_{01*2} & \\ \tau_{01*2} + a\tau_{11*2} & \tau_{11*2} \end{bmatrix} \right) \\
 &= \text{tr} \left( \begin{bmatrix} 0 & 0 \\ \text{var}(x_{ijk})\tau_{01*2} + \text{var}(x_{ijk})a\tau_{11*2} & \text{var}(x_{ijk})\tau_{11*2} \end{bmatrix} \right) \\
 &= \text{var}(x_{ijk})\tau_{11*2}
 \end{aligned}$$

(OC38)

The total variance attributable to  $v_{1*3}$  is

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$$\begin{aligned}
 tr(\Sigma_{1*3} \mathbf{T}_3) &= tr \left( \begin{bmatrix} 0 & & \\ 0 & \text{var}(x_{ijk}) & \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \tau_{00*3} + a^2\tau_{11*3} + b^2\tau_{22*3} & & \\ \tau_{01*3} + a\tau_{11*3} + b\tau_{12*3} & \tau_{11*3} & \\ \tau_{02*3} + a\tau_{12*3} + b\tau_{22*3} & \tau_{12*3} & \tau_{22*3} \end{bmatrix} \right) \\
 &= tr \left( \begin{bmatrix} 0 & 0 & 0 \\ \text{var}(x_{ijk})(\tau_{01*3} + a\tau_{11*3} + b\tau_{12*3}) & \text{var}(x_{ijk})\tau_{11*3} & \text{var}(x_{ijk})(\tau_{02*3} + a\tau_{12*3} + b\tau_{22*3}) \\ 0 & 0 & 0 \end{bmatrix} \right) \\
 &= \text{var}(x_{ijk})\tau_{11*3}
 \end{aligned} \tag{OC39}$$

The total variance attributable to  $v_{2*2}$  is

$$\begin{aligned}
 tr(\Sigma_{2*2} \mathbf{T}_2) &= tr \left( \begin{bmatrix} 0 & \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \tau_{00*2} + a^2\tau_{11*2} + 2a\tau_{01*2} & \\ \tau_{01*2} + a\tau_{11*2} & \tau_{11*2} \end{bmatrix} \right) \\
 &= tr \left( \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \right) \\
 &= 0
 \end{aligned} \tag{OC40}$$

The total variance attributable to  $v_{2*3}$  is

$$\begin{aligned}
 tr(\Sigma_{2*3} \mathbf{T}_3) &= tr \left( \begin{bmatrix} 0 & & \\ 0 & 0 & \\ 0 & 0 & \text{var}(w_{jk}) \end{bmatrix} \begin{bmatrix} \tau_{00*3} + a^2\tau_{11*3} + b^2\tau_{22*3} & & \\ \tau_{01*3} + a\tau_{11*3} + b\tau_{12*3} & \tau_{11*3} & \\ \tau_{02*3} + a\tau_{12*3} + b\tau_{22*3} & \tau_{12*3} & \tau_{22*3} \end{bmatrix} \right) \\
 &= tr \left( \begin{bmatrix} 0 & & \\ 0 & 0 & \\ \text{var}(w_{jk})(\tau_{02*3} + a\tau_{12*3} + b\tau_{22*3}) & \text{var}(w_{jk})\tau_{12*3} & \text{var}(w_{jk})\tau_{22*3} \end{bmatrix} \right) \\
 &= \text{var}(w_{jk})\tau_{22*3}
 \end{aligned} \tag{OC41}$$

The total variance attributable to  $v_{3*2}$  is

$$\begin{aligned}
 tr(\Sigma_{3*2} \mathbf{T}_2) &= tr \left( \begin{bmatrix} 0 & \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \tau_{00*2} + a^2\tau_{11*2} + 2a\tau_{01*2} & \\ \tau_{01*2} + a\tau_{11*2} & \tau_{11*2} \end{bmatrix} \right) \\
 &= tr \left( \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \right) \\
 &= 0
 \end{aligned} \tag{OC42}$$

The total variance attributable to  $v_{3*3}$  is

$$\begin{aligned}
 tr(\Sigma_{3*3} \mathbf{T}_3) &= tr \left( \begin{bmatrix} 0 & & \\ 0 & 0 & \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \tau_{00*3} + a^2\tau_{11*3} + b^2\tau_{22*3} & & \\ \tau_{01*3} + a\tau_{11*3} + b\tau_{12*3} & \tau_{11*3} & \\ \tau_{02*3} + a\tau_{12*3} + b\tau_{22*3} & \tau_{12*3} & \tau_{22*3} \end{bmatrix} \right) \\
 &= tr \left( \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \right) \\
 &= 0
 \end{aligned} \tag{OC43}$$

The total variance attributable to  $m_2$  is

$$\begin{aligned}
 \mathbf{m}'_{1*2} \mathbf{T}_2 \mathbf{m}_{1*2} + \mathbf{m}'_{2*2} \mathbf{T}_2 \mathbf{m}_{2*2} + \mathbf{m}'_{3*2} \mathbf{T}_2 \mathbf{m}_{3*2} &= \begin{bmatrix} 0 & 0 \end{bmatrix} \begin{bmatrix} \tau_{00*2} + a^2\tau_{11*2} + 2a\tau_{01*2} & \\ \tau_{01*2} + a\tau_{11*2} & \tau_{11*2} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \end{bmatrix} \\
 &+ \begin{bmatrix} 0 \\ 0 \end{bmatrix} \begin{bmatrix} \tau_{00*2} + a^2\tau_{11*2} + 2a\tau_{01*2} & \\ \tau_{01*2} + a\tau_{11*2} & \tau_{11*2} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \end{bmatrix} \\
 &+ \begin{bmatrix} 1 & -a \end{bmatrix} \begin{bmatrix} \tau_{00*2} + a^2\tau_{11*2} + 2a\tau_{01*2} & \\ \tau_{01*2} + a\tau_{11*2} & \tau_{11*2} \end{bmatrix} \begin{bmatrix} 1 \\ -a \end{bmatrix} \\
 &= 0 + 0 + \begin{bmatrix} \tau_{00*2} + a^2\tau_{11*2} + 2a\tau_{01*2} - a\tau_{01*2} - a^2\tau_{11*2} & \tau_{01*2} + a\tau_{11*2} - a\tau_{11*2} \end{bmatrix} \begin{bmatrix} 1 \\ -a \end{bmatrix} \\
 &= \tau_{00*2} + a^2\tau_{11*2} + 2a\tau_{01*2} - a\tau_{01*2} - a^2\tau_{11*2} - a\tau_{01*2} - a^2\tau_{11*2} + a^2\tau_{11*2} \\
 &= \tau_{00*2} + (a^2 - a^2 - a^2 + a^2)\tau_{11*2} + (2a - a - a)\tau_{01*2} \\
 &= \tau_{00*2}
 \end{aligned} \tag{OC44}$$

And the total variance attributable to  $m_3$  is

$$\begin{aligned}
 \mathbf{m}'_{1*3} \mathbf{T}_3 \mathbf{m}_{1*3} + \mathbf{m}'_{2*3} \mathbf{T}_3 \mathbf{m}_{2*3} + \mathbf{m}'_{3*3} \mathbf{T}_3 \mathbf{m}_{3*3} &= \begin{bmatrix} 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \tau_{00*3} + a^2\tau_{11*3} + b^2\tau_{22*3} + 2a\tau_{01*3} + 2b\tau_{02*3} + 2ab\tau_{12*3} & & \\ \tau_{01*3} + a\tau_{11*3} + b\tau_{12*3} & \tau_{11*3} & \\ \tau_{02*3} + a\tau_{12*3} + b\tau_{22*3} & \tau_{12*3} & \tau_{22*3} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \\
 &+ \begin{bmatrix} 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \tau_{00*3} + a^2\tau_{11*3} + b^2\tau_{22*3} + 2a\tau_{01*3} + 2b\tau_{02*3} + 2ab\tau_{12*3} & & \\ \tau_{01*3} + a\tau_{11*3} + b\tau_{12*3} & \tau_{11*3} & \\ \tau_{02*3} + a\tau_{12*3} + b\tau_{22*3} & \tau_{12*3} & \tau_{22*3} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \\
 &+ \begin{bmatrix} 1 & -a & -b \end{bmatrix} \begin{bmatrix} \tau_{00*3} + a^2\tau_{11*3} + b^2\tau_{22*3} + 2a\tau_{01*3} + 2b\tau_{02*3} + 2ab\tau_{12*3} & & \\ \tau_{01*3} + a\tau_{11*3} + b\tau_{12*3} & \tau_{11*3} & \\ \tau_{02*3} + a\tau_{12*3} + b\tau_{22*3} & \tau_{12*3} & \tau_{22*3} \end{bmatrix} \begin{bmatrix} 1 \\ -a \\ -b \end{bmatrix} \\
 &= 0 + 0 + \begin{bmatrix} \tau_{00*3} + a^2\tau_{11*3} + b^2\tau_{22*3} + 2a\tau_{01*3} + 2b\tau_{02*3} + 2ab\tau_{12*3} - a(\tau_{01*3} + a\tau_{11*3} + b\tau_{12*3}) - b(\tau_{02*3} + a\tau_{12*3} + b\tau_{22*3}) & & \\ \tau_{01*3} + a\tau_{11*3} + b\tau_{12*3} - a\tau_{11*3} - b\tau_{12*3} & \tau_{11*3} & \\ \tau_{02*3} + a\tau_{12*3} + b\tau_{22*3} - a\tau_{12*3} - b\tau_{22*3} & \tau_{12*3} & \tau_{22*3} \end{bmatrix} \begin{bmatrix} 1 \\ -a \\ -b \end{bmatrix} \\
 &= \tau_{00*3} + a^2\tau_{11*3} + b^2\tau_{22*3} + 2a\tau_{01*3} + 2b\tau_{02*3} + 2ab\tau_{12*3} - a(\tau_{01*3} + a\tau_{11*3} + b\tau_{12*3}) - b(\tau_{02*3} + a\tau_{12*3} + b\tau_{22*3}) \\
 &\quad - a(\tau_{01*3} + a\tau_{11*3} + b\tau_{12*3} - a\tau_{11*3} - b\tau_{12*3}) - b(\tau_{02*3} + a\tau_{12*3} + b\tau_{22*3} - a\tau_{12*3} - b\tau_{22*3}) \\
 &= \tau_{00*3} + a^2\tau_{11*3} + b^2\tau_{22*3} + 2a\tau_{01*3} + 2b\tau_{02*3} + 2ab\tau_{12*3} - a\tau_{01*3} - a^2\tau_{11*3} - ab\tau_{12*3} - b\tau_{02*3} - ab\tau_{12*3} - b^2\tau_{22*3} \\
 &\quad - a\tau_{01*3} - a^2\tau_{11*3} - ab\tau_{12*3} + a^2\tau_{11*3} + ab\tau_{12*3} - b\tau_{02*3} - ab\tau_{12*3} - b^2\tau_{22*3} + ab\tau_{12*3} + b^2\tau_{22*3} \\
 &= \tau_{00*3} + (a^2 - a^2 - a^2 + a^2)\tau_{11*3} + (b^2 - b^2 - b^2 + b^2)\tau_{22*3} + (-a - a + 2a)\tau_{01*3} + (-b - b + 2b)\tau_{02*3} + (-ab - ab - ab + ab - ab + ab + 2ab)\tau_{12*3} \\
 &= \tau_{00*3}
 \end{aligned} \tag{OC45}$$

Adding each of these individual variances together yields the following the model-implied total variance for the *centered-by-constant model*:

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$$\begin{aligned} \text{var}(y_{ijk}) = & \gamma_1^2 \text{var}(x_{ijk}) + \gamma_2^2 \text{var}(w_{jk}) + \gamma_3^2 \text{var}(z_k) \\ & + \tau_{11*2} \text{var}(x_{ijk}) + \tau_{11*3} \text{var}(x_{ijk}) + \tau_{22*3} \text{var}(w_{jk}) + \tau_{00*2} + \tau_{00*3} + \sigma^2 \end{aligned} \quad (\text{OC46})$$

Adding the level-1 variances yields the model-implied level-1 outcome variance:

$$\text{var}_{ijk}(y_{ijk}) = \gamma_1^2 \text{var}(x_{ijk}) + \tau_{11*2} \text{var}(x_{ijk}) + \tau_{11*3} \text{var}(x_{ijk}) + \sigma^2 \quad (\text{OC47})$$

Adding the level-2 variances yields the model-implied level-2 outcome variance:

$$\text{var}_{jk}(y_{ijk}) = \gamma_2^2 \text{var}(w_{jk}) + \tau_{22*3} \text{var}(w_{jk}) + \tau_{00*2} \quad (\text{OC48})$$

And adding the level-3 variances yields the model-implied level-3 outcome variance:

$$\text{var}_k(y_{ijk}) = \gamma_3^2 \text{var}(z_k) + \tau_{00*3} \quad (\text{OC49})$$

We can thus form the following total R-squared measures for the *centered-by-constant model* as such, using the formulas provided for non-cluster-mean-centered models in Table 5 (here we used asterisks to distinguish these R-squared measures from the measures computed for the *mean-centered model*, with the latter denoted without an asterisk):

$$\begin{aligned} R_t^{2(f_1)*} &= \frac{\gamma_1^2 \text{var}(x_{ijk})}{\text{Eqn OC46}} = R_t^{2(f_1)} \\ R_t^{2(f_2)*} &= \frac{\gamma_2^2 \text{var}(w_{jk})}{\text{Eqn OC46}} = R_t^{2(f_2)} \\ R_t^{2(f_3)*} &= \frac{\gamma_3^2 \text{var}(z_k)}{\text{Eqn OC46}} = R_t^{2(f_3)} \\ R_t^{2(v_{1*2})*} &= \frac{\tau_{11*2} \text{var}(x_{ijk})}{\text{Eqn OC46}} = R_t^{2(v_{1*2})} \\ R_t^{2(v_{1*3})*} &= \frac{\tau_{11*3} \text{var}(x_{ijk})}{\text{Eqn OC46}} = R_t^{2(v_{1*3})} \\ R_t^{2(v_{2*2})*} &= 0 \\ R_t^{2(v_{2*3})*} &= \frac{\tau_{22*3} \text{var}(w_{jk})}{\text{Eqn OC46}} = R_t^{2(v_{2*3})} \\ R_t^{2(v_{3*2})*} &= 0 \\ R_t^{2(v_{3*3})*} &= 0 \\ R_t^{2(m_2)*} &= \frac{\tau_{00*2}}{\text{Eqn OC46}} = R_t^{2(m_2)} \\ R_t^{2(m_3)*} &= \frac{\tau_{00*3}}{\text{Eqn OC46}} = R_t^{2(m_3)} \end{aligned} \quad (\text{OC50})$$

We can similarly form the following level-specific measures:

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$$R_1^{2(f_1)*} = \frac{\gamma_1^2 \text{var}(x_{ijk})}{\text{Eqn OC47}} = R_1^{2(f_1)}$$

$$R_2^{2(f_2)*} = \frac{\gamma_2^2 \text{var}(w_{jk})}{\text{Eqn OC48}} = R_2^{2(f_2)}$$

$$R_3^{2(f_3)*} = \frac{\gamma_3^2 \text{var}(z_k)}{\text{Eqn OC49}} = R_3^{2(f_3)}$$

$$R_1^{2(v_{1*2})*} = \frac{\tau_{11*2} \text{var}(x_{ijk})}{\text{Eqn OC47}} = R_1^{2(v_{1*2})}$$

$$R_1^{2(v_{1*3})*} = \frac{\tau_{11*3} \text{var}(x_{ijk})}{\text{Eqn OC47}} = R_1^{2(v_{1*3})}$$

$$R_2^{2(v_{2*2})*} = 0$$

$$R_2^{2(v_{2*3})*} = \frac{\tau_{22*3} \text{var}(w_{jk})}{\text{Eqn OC48}} = R_2^{2(v_{2*3})}$$

$$R_3^{2(v_{3*2})*} = 0$$

$$R_3^{2(v_{3*3})*} = 0$$

$$R_2^{2(m_2)*} = \frac{\tau_{00*2}}{\text{Eqn OC48}} = R_2^{2(m_2)}$$

$$R_3^{2(m_3)*} = \frac{\tau_{00*3}}{\text{Eqn OC49}} = R_3^{2(m_3)} \tag{OC51}$$

Hence, each measure computed for the *mean-centered model* is exactly equivalent to the corresponding measure computed for the *centered-by-constant model*, while each measure computed for the *centered-by-constant model* that is not applicable to the *mean-centered model* (i.e.,  $R_1^{2(v_{2*2})*}$ ,  $R_1^{2(v_{3*2})*}$ ,  $R_1^{2(v_{2*3})*}$ ,  $R_1^{2(v_{3*3})*}$ ) is equal to 0.

### Online Appendix D: *r2mlm3* R function

Here we describe and provide the R code for the *r2mlm3* function. This function has now also been inserted into the *r2mlm* R package (Shaw, Rights, Sterba, & Flake, 2020) on CRAN.

#### ***r2mlm3* R function Description:**

This function reads in raw data and three-level multilevel model (MLM) parameter estimates and outputs all relevant  $R^2$  measures as well as an accompanying bar chart. That is, when entering results from a cluster-mean-centered model (i.e., a model in which all level-1 and level-2 predictors are cluster-mean-centered, using the method for cluster-mean-centering described in the manuscript), this function outputs all total and level-specific measures in Table 1 with an accompanying barchart (e.g., Figure 1). When entering *non*-cluster-mean-centered model results (i.e., results from a model in which *at least one* level-1 or level-2 predictor is *not* cluster-mean-centered), the function outputs all total and level-specific measures from Table 5 with an accompanying bar chart. For each type of model, any number of predictors is supported. Any of the predictors at level-1 or any intermediate level (i.e., levels below the highest level) can have random slopes across any higher-level unit.

This *r2mlm3* function can also accommodate two-level models. To input results for two-level models, set the following arguments equal to NULL: *l3\_covs*, *random\_covs13*, *random\_covs23*, *gamma\_3*, *Tau13*, *Tau23*.

#### ***r2mlm3* R function Input:**

*data* – Dataset with rows denoting observations and columns denoting variables

*clustermeancentered* – By default, this argument is set to TRUE, indicating that cluster-mean-centered model results are being inputted. When instead entering non-cluster-mean-centered model results, set this argument to FALSE. Additionally, for non-cluster-mean-centered model results, random effect variances/covariances are to be entered in arguments *Tau2\_noncmc* and *Tau3\_noncmc* (defined below), rather than in the *Tau12*, *Tau13*, and *Tau23* arguments used for cluster-mean-centered model results. Additionally, when entering non-cluster-mean-centered model results, user must specify *l2clusterID\_noncmc* and *l3clusterID\_noncmc* (neither of which are necessary for cluster-mean-centered model results). Function input is otherwise the same for cluster-mean-centered and non-cluster-mean-centered model results.

*l1\_covs* – Vector of numbers (or variable names) corresponding to the columns in the dataset of the level-1 predictors used in the MLM (if none used, set to NULL)

*l2\_covs* – Vector of numbers (or variable names) corresponding to the columns in the dataset of the level-2 predictors used in the MLM (if none used, set to NULL)

*l3\_covs* – Vector of numbers (or variable names) corresponding to the columns in the dataset of the level-3 predictors used in the MLM (if none used, set to NULL)

*random\_covs12* – Vector of numbers (or variable names) corresponding to the columns in the dataset of the level-1 predictors that have random slopes across level-2 units in the MLM (if no such random slopes, set to NULL)

*random\_covs13* – Vector of numbers (or variable names) corresponding to the columns in the dataset

- of the level-1 predictors that have random slopes across level-3 units in the MLM (if no such random slopes, set to NULL)
- random\_covs23* – Vector of numbers (or variable names) corresponding to the columns in the dataset of the level-2 predictors that have random slopes across level-3 units in the MLM (if no such random slopes, set to NULL)
- gamma\_1* – Vector of fixed slope estimates for all level-1 predictors, to be entered in the order of the predictors listed by *l1\_covs* (if none, set to NULL)
- gamma\_2* – Vector of fixed slope estimates for all level-2 predictors, to be entered in the order listed by *l2\_covs* (if none, set to NULL)
- gamma\_3* – Vector of fixed slope estimates for all level-3 predictors, to be entered in the order listed by *l3\_covs* (if none, set to NULL)
- Tau12* – for cluster-mean-centered model results (set to NULL if entering non-cluster-mean-centered model results), this is the random effect covariance matrix with the first row/column denoting the intercept variance and covariances across level-2 units and each subsequent row/column denotes a given level-1 predictor's random slope variance and covariances across level-2 units (to be entered in the order listed by *random\_covs12*; if none, set to NULL)
- Tau13* – for cluster-mean-centered model results (set to NULL if entering non-cluster-mean-centered model results), this is the random effect covariance matrix with the first row/column denoting the intercept variance and covariances across level-3 units and each subsequent row/column denotes a given level-1 predictor's random slope variance and covariances across level-3 units (to be entered in the order listed by *random\_covs13*; if none, set to NULL)
- Tau23* – for cluster-mean-centered model results (set to NULL if entering non-cluster-mean-centered model results), this is the random effect covariance matrix with each row/column denoting a given level-2 predictor's random slope variance and covariances across level-3 units (to be entered in the order listed by *random\_covs23*; if none, set to NULL)
- Tau2\_noncmc* – For non-cluster-mean-centered model results, this is the level-2 random effect covariance matrix; the first row/column denotes the intercept variance and covariances across level-2 units and each subsequent row/column denotes a given predictor's random slope variance and covariances across level-2 units (to be entered in the order listed by *randomcovsl2\_noncmc*; by default, this argument is set to NULL).
- Tau3\_noncmc* – For non-cluster-mean-centered model results, this is the level-3 random effect covariance matrix; the first row/column denotes the intercept variance and covariances across level-3 units and each subsequent row/column denotes a given predictor's random slope variance and covariances across level-3 units (to be entered in the order listed by *randomcovsl2\_noncmc*; by default, this argument is set to NULL).
- l2clusterID\_noncmc* – For non-cluster-mean-centered model results, this is the number (or variable name) corresponding to the column in the dataset containing the level-2 cluster identification (function assumes that each level-2 cluster ID is unique; by default, this argument is set to NULL)
- l3clusterID\_noncmc* – For non-cluster-mean-centered model results, this is the number (or variable name) corresponding to the column in the dataset containing the level-3 cluster identification (function assumes that each level-3 cluster ID is unique; by default, this argument is set to NULL)



NULL)

$\sigma_2$  – level-1 residual variance

### **r2mlm3 R function Code:**

```
r2mlm3<- function(data,l1_covs,l2_covs,l3_covs,random_covs12,random_covs13,random_covs23,
  gamma_1,gamma_2,gamma_3,Tau12,Tau13,Tau23,sigma2,
  clustermeancentered=TRUE, Tau2_noncmc=NULL,Tau3_noncmc=NULL,
  l2clusterID_noncmc=NULL,l3clusterID_noncmc=NULL){

  if(clustermeancentered==TRUE){

    ##compute phis
    if(is.null(l1_covs)==T){
      phi_1 <- 0
      gamma_1 <- 0
    }else{
      phi_1 <- var(data[,l1_covs],na.rm=T)}
    if(is.null(l2_covs)==T){
      phi_2 <- 0
      gamma_2 <- 0
    }else{
      phi_2 <- var(data[,l2_covs],na.rm=T)}
    if(is.null(l3_covs)==T){
      phi_3 <- 0
      gamma_3 <- 0
    }else{
      phi_3 <- var(data[,l3_covs],na.rm=T)}

    ##compute variances/covariances of random components

    if(is.null(Tau13)==TRUE) Tau13 <- matrix(c(0),1,1)

    if(is.null(random_covs12)==F){
      var_randomcovs12 <- var(cbind(1,data[,c(random_covs12)]),na.rm=T)
      psi12 <- matrix(c(diag(Tau12)),ncol=1)
      kappa12 <- matrix(c(Tau12[lower.tri(Tau12)==TRUE]),ncol=1)
      v12 <- matrix(c(diag(var_randomcovs12)),ncol=1)
      r12 <- matrix(c(var_randomcovs12[lower.tri(var_randomcovs12)==TRUE]),ncol=1)
    }else{
      var_randomcovs12 <- 0
      psi12 <- 0
      kappa12 <- 0
      v12 <- 0
      r12 <- 0
    }

    if(is.null(random_covs13)==F){
      var_randomcovs13 <- var(cbind(1,data[,c(random_covs13)]),na.rm=T)
      psi13 <- matrix(c(diag(Tau13)),ncol=1)
      kappa13 <- matrix(c(Tau13[lower.tri(Tau13)==TRUE]),ncol=1)
      v13 <- matrix(c(diag(var_randomcovs13)),ncol=1)
      r13 <- matrix(c(var_randomcovs13[lower.tri(var_randomcovs13)==TRUE]),ncol=1)
    }else{
      var_randomcovs13 <- 0
```

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```

psi13 <- 0
kappa13 <- 0
v13 <- 0
r13 <- 0
}

if(is.null(random_covs23)==F){
var_randomcovs23 <- var(cbind(data[,c(random_covs23)],na.rm=T)
psi23 <- matrix(c(diag(Tau23)),ncol=1)
kappa23 <- matrix(c(Tau23[lower.tri(Tau23)==TRUE]),ncol=1)
v23 <- matrix(c(diag(var_randomcovs23)),ncol=1)
r23 <- matrix(c(var_randomcovs23[lower.tri(var_randomcovs23)==TRUE]),ncol=1)
}else{
var_randomcovs23 <- 0
psi23 <- 0
kappa23 <- 0
v23 <- 0
r23 <- 0
}

##compute level-specific and total variance

l1var <- (t(gamma_1)%*%phi_1%*%gamma_1) + (t(v12)%*%psi12 + 2*(t(r12)%*%kappa12)) + (t(v13)%*%psi13 +
2*(t(r13)%*%kappa13))+ sigma2

l2var <-(t(gamma_2)%*%phi_2%*%gamma_2) + (t(v23)%*%psi23 + 2*(t(r23)%*%kappa23)) + Tau12[1,1]

l3var <- (t(gamma_3)%*%phi_3%*%gamma_3) + Tau13[1,1]

totalvar <- l1var + l2var + l3var

#total R2 measures

R2_f1_t <- (t(gamma_1)%*%phi_1%*%gamma_1)/totalvar
R2_f2_t <- (t(gamma_2)%*%phi_2%*%gamma_2)/totalvar
R2_f3_t <- (t(gamma_3)%*%phi_3%*%gamma_3)/totalvar
R2_v12_t <- (t(v12)%*%psi12 + 2*(t(r12)%*%kappa12)) /totalvar
R2_v13_t <- (t(v13)%*%psi13 + 2*(t(r13)%*%kappa13))/totalvar
R2_v23_t <- (t(v23)%*%psi23 + 2*(t(r23)%*%kappa23)) /totalvar
R2_m2_t <- Tau12[1,1] /totalvar
R2_m3_t <- Tau13[1,1]/totalvar

#l1 R2 measures
R2_f1_1 <- (t(gamma_1)%*%phi_1%*%gamma_1) /l1var
R2_v12_1 <- (t(v12)%*%psi12 + 2*(t(r12)%*%kappa12)) /l1var
R2_v13_1 <- (t(v13)%*%psi13 + 2*(t(r13)%*%kappa13))/l1var

#l2 R2 measures
R2_f2_2 <-(t(gamma_2)%*%phi_2%*%gamma_2)/l2var
R2_v23_2 <- (t(v23)%*%psi23 + 2*(t(r23)%*%kappa23)) /l2var
R2_m2_2 <- Tau12[1,1]/l2var

#l3 R2 measures
R2_f3_3 <- (t(gamma_3)%*%phi_3%*%gamma_3)/l3var
R2_m3_3 <- Tau13[1,1]/l3var

R2_table <- matrix(c(R2_f1_t,R2_f2_t,R2_f3_t,R2_v12_t,R2_v13_t,R2_v23_t,R2_m2_t,R2_m3_t,
R2_f1_1,"NA","NA",R2_v12_1,R2_v13_1,"NA","NA","NA",
"NA",R2_f2_2,"NA","NA","NA",R2_v23_2,R2_m2_2,"NA",
"NA","NA",R2_f3_3,"NA","NA","NA","NA",R2_m3_3)
,ncol=4)
rownames(R2_table) <- c("f1","f2","f3","v12","v13","v23","m2","m3")

```

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```

colnames(R2_table) <- c("total","I1","I2","I3")

##barchart

contributions_stacked <-
  matrix(c(R2_f1_t,R2_f2_t,R2_f3_t,R2_v12_t,R2_v13_t,R2_v23_t,R2_m2_t,R2_m3_t,sigma2/totalvar,
          R2_f1_1,0,0,R2_v12_1,R2_v13_1,0,0,0,sigma2/11var,
          0,R2_f2_2,0,0,0,R2_v23_2,R2_m2_2,0,0,
          0,0,R2_f3_3,0,0,0,0,R2_m3_3,0),nrow=9,ncol=4)
colnames(contributions_stacked) <- c("total","level-1","level-2","level-3")
rownames(contributions_stacked) <- c("f1","f2","f3",
                                     "v12","v13","v23",
                                     "m2","m3","resid")

barplot(contributions_stacked, main="Decomposition", horiz=FALSE,

        ylim=c(0,1),col=c("darkred","steelblue","darkgoldenrod1","darkred","darkred","midnightblue","midnightblue","darkgoldenrod1","white"),
        ylab="proportion of variance",
        density=c(NA,NA,NA,20,40,20,40,20,NA),angle=c(0,0,0,45,45,135,135,0,0))

        legend(4.89,.7,title="source",legend=rownames(contributions_stacked),fill=c("darkred","steelblue","darkgoldenrod1","darkred","darkred","midnightblue","midnightblue","darkgoldenrod1","white"),
        cex=.7, pt.cex = 1, xpd=TRUE,density=c(NA,NA,NA,30,50,30,50,30,NA),angle=c(0,0,0,45,45,135,135,0,0))

Output <- list(noquote(R2_table))
names(Output) <- c("R2s")
}

if(clustermeancentered==FALSE){

allfixedcovs_noncmc<- c(I1_covs,I2_covs,I3_covs)
allgamma_noncmc <- c(gamma_1,gamma_2,gamma_3)
randomcovsl2_noncmc <- random_covs12
randomcovsl3_noncmc <- c(random_covs13,random_covs23)

##create version of dataset that decomposes predictors into level-specific portions

data_temp <- data

if(is.null(allfixedcovs_noncmc)==F){
  data_fixed_centered <- matrix(NA,nrow(data),length(allfixedcovs_noncmc)*3)
  colnames(data_fixed_centered) <- c(paste0("p",seq(length(allfixedcovs_noncmc)),"_I1"),
                                     paste0("p",seq(length(allfixedcovs_noncmc)),"_I2"),
                                     paste0("p",seq(length(allfixedcovs_noncmc)),"_I3"))

  if(length(I2_covs)>0){
    data_fixed_centered[, (length(I1_covs)+1):(length(allfixedcovs_noncmc))] <- 0
  }

  if(length(I3_covs)>0){

    data_fixed_centered[, (length(allfixedcovs_noncmc)+length(I1_covs)+length(I2_covs)+1):(2*length(allfixedcovs_noncmc))] <- 0
    data_fixed_centered[, (length(I1_covs)+1):(length(allfixedcovs_noncmc))] <- 0
  }
}

if(is.null(randomcovsl2_noncmc)==F){
  data_randoml2_centered <- matrix(NA,nrow(data),length(randomcovsl2_noncmc)*3)
  colnames(data_randoml2_centered) <- c(paste0("p",seq(length(randomcovsl2_noncmc)),"_I1"),

```

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        paste0("p",seq(length(randomcovsl2_noncmc)),"_l2"),
        paste0("p",seq(length(randomcovsl2_noncmc)),"_l3"))
    }

    if(is.null(randomcovsl3_noncmc)==F){
    data_randoml3_centered <- matrix(NA,nrow(data),length(randomcovsl3_noncmc)*3)
    colnames(data_randoml3_centered) <- c(paste0("p",seq(length(randomcovsl3_noncmc)),"_l1"),
        paste0("p",seq(length(randomcovsl3_noncmc)),"_l2"),
        paste0("p",seq(length(randomcovsl3_noncmc)),"_l3"))
    }

    ##loop through level-2 clusters
    for(clus2 in seq(max(as.numeric(data[,l2clusterID_noncmc])))){

    for(i in seq(nrow(data))){

        if(data[i,l2clusterID_noncmc]==clus2){

            if(is.null(allfixedcovs_noncmc)==F){
            for(ncov in seq(length(allfixedcovs_noncmc))){
                ##compute level-1 portion of predictor
                data_fixed_centered[i,paste0("p",ncov,"_l1")] <- data[i,allfixedcovs_noncmc[ncov]]-
                    mean(data_temp[which(data_temp[,l2clusterID_noncmc]==clus2),allfixedcovs_noncmc[ncov]],na.rm=T)
                ##compute level-2 portion of predictor
                data_fixed_centered[i,paste0("p",ncov,"_l2")] <-
                    mean(data_temp[which(data_temp[,l2clusterID_noncmc]==clus2),allfixedcovs_noncmc[ncov]],na.rm=T)
            }
            }

            if(is.null(randomcovsl2_noncmc)==F){
            for(ncov in seq(length(randomcovsl2_noncmc))){
                ##compute level-1 portion of predictor
                data_randoml2_centered[i,paste0("p",ncov,"_l1")] <- data[i,randomcovsl2_noncmc[ncov]]-
                    mean(data_temp[which(data_temp[,l2clusterID_noncmc]==clus2),randomcovsl2_noncmc[ncov]],na.rm=T)
                ##compute level-2 portion of predictor
                data_randoml2_centered[i,paste0("p",ncov,"_l2")] <-
                    mean(data_temp[which(data_temp[,l2clusterID_noncmc]==clus2),randomcovsl2_noncmc[ncov]],na.rm=T)
            }
            }

            if(is.null(randomcovsl3_noncmc)==F){
            for(ncov in seq(length(randomcovsl3_noncmc))){
                ##compute level-1 portion of predictor
                data_randoml3_centered[i,paste0("p",ncov,"_l1")] <- data[i,randomcovsl3_noncmc[ncov]]-
                    mean(data_temp[which(data_temp[,l2clusterID_noncmc]==clus2),randomcovsl3_noncmc[ncov]],na.rm=T)
                ##compute level-2 portion of predictor
                data_randoml3_centered[i,paste0("p",ncov,"_l2")] <-
                    mean(data_temp[which(data_temp[,l2clusterID_noncmc]==clus2),randomcovsl3_noncmc[ncov]],na.rm=T)
            }
            }
        }
    }
    }

    ##loop through level-3 clusters
    for(clus3 in seq(max(as.numeric(data[,l3clusterID_noncmc])))){

    for(i in seq(nrow(data))){

        if(data[i,"schoolid"]==clus3){

```

```

if(is.null(allfixedcovs_noncmc)==F){
for(ncov in seq(length(allfixedcovs_noncmc))){
  ##compute level-3 portion of predictor
  data_fixed_centered[i,paste0("p",ncov,"_l3")] <-
    mean(data_temp[which(data_temp[,l3clusterID_noncmc]==clus3),allfixedcovs_noncmc[ncov]],na.rm=T)
}
}

if(is.null(randomcovsl2_noncmc)==F){
for(ncov in seq(length(randomcovsl2_noncmc))){
  ##compute level-3 portion of predictor
  data_randoml2_centered[i,paste0("p",ncov,"_l3")] <-
    mean(data_temp[which(data_temp[,l3clusterID_noncmc]==clus3),randomcovsl2_noncmc[ncov]],na.rm=T)
}
}

if(is.null(randomcovsl3_noncmc)==F){
for(ncov in seq(length(randomcovsl3_noncmc))){
  ##compute level-3 portion of predictor
  data_randoml3_centered[i,paste0("p",ncov,"_l3")] <-
    mean(data_temp[which(data_temp[,l3clusterID_noncmc]==clus3),randomcovsl3_noncmc[ncov]],na.rm=T)
}
}
}
}

if(is.null(allfixedcovs_noncmc)==F){
for(ncov in seq(length(allfixedcovs_noncmc))){
  ##cluster-mean-center level-2 predictor
  data_fixed_centered[,paste0("p",ncov,"_l2")] <- data_fixed_centered[,paste0("p",ncov,"_l2")] -
    data_fixed_centered[,paste0("p",ncov,"_l3")]
}
}

if(is.null(randomcovsl2_noncmc)==F){
for(ncov in seq(length(randomcovsl2_noncmc))){
  ##cluster-mean-center level-2 predictor
  data_randoml2_centered[,paste0("p",ncov,"_l2")] <- data_randoml2_centered[,paste0("p",ncov,"_l2")] -
    data_randoml2_centered[,paste0("p",ncov,"_l3")]
}
}

if(is.null(randomcovsl3_noncmc)==F){
for(ncov in seq(length(randomcovsl3_noncmc))){
  ##cluster-mean-center level-2 predictor
  data_randoml3_centered[,paste0("p",ncov,"_l2")] <- data_randoml3_centered[,paste0("p",ncov,"_l2")] -
    data_randoml3_centered[,paste0("p",ncov,"_l3")]
}
}

##make lower-level portions of cluster-level predictors equal to 0
if(is.null(allfixedcovs_noncmc)==F){
  if(length(l2_covs)>0){
    data_fixed_centered[(length(l1_covs)+1):(length(allfixedcovs_noncmc))] <- 0
  }

  if(length(l3_covs)>0){
    data_fixed_centered[(length(allfixedcovs_noncmc)+length(l1_covs)+length(l2_covs)+1):(2*length(allfixedcovs_noncmc))] <- 0
  }
}

```

```

data_fixed_centered[(length(l1_covs)+1):(length(allfixedcovs_noncmc))] <- 0
}
}

if(is.null(allfixedcovs_noncmc)==F){
##compute phis
phi1 <- var(data_fixed_centered[,seq(length(allfixedcovs_noncmc))],na.rm=T)
phi2 <- var(data_fixed_centered[,c(length(allfixedcovs_noncmc)+seq(length(allfixedcovs_noncmc)))],na.rm=T)
phi3 <- var(data_fixed_centered[,c(2*length(allfixedcovs_noncmc)+seq(length(allfixedcovs_noncmc)))],na.rm=T)

##compute variance explained by fs
f1 <- t(allgamma_noncmc)%*%phi1%*%allgamma_noncmc
f2 <- t(allgamma_noncmc)%*%phi2%*%allgamma_noncmc
f3 <- t(allgamma_noncmc)%*%phi3%*%allgamma_noncmc
}else{
  f1 <-f2<-f3<-0
}

##make lower-level portions of cluster-level predictors equal to 0
if(is.null(randomcovs13_noncmc)==F){
  if(length(random_covs23)>0){
    data_random13_centered[(length(random_covs13)+1):(length(randomcovs13_noncmc))] <- 0
  }
}

if(is.null(randomcovs12_noncmc)==F){
##compute Sigmas
Sigma12 <- var(cbind(0,data_random12_centered[,seq(length(randomcovs12_noncmc))],na.rm=T)
Sigma22 <-
  var(cbind(0,data_random12_centered[,c(length(randomcovs12_noncmc)+seq(length(randomcovs12_noncmc)))],na.r
m=T)
Sigma32 <-
  var(cbind(0,data_random12_centered[,c(2*length(randomcovs12_noncmc)+seq(length(randomcovs12_noncmc)))],n
a.rm=T)

##compute variance explained by vs
v12<- as.numeric(sum(diag(Sigma12%*%Tau2_noncmc)))
v22<- as.numeric(sum(diag(Sigma22%*%Tau2_noncmc)))
v32<- as.numeric(sum(diag(Sigma32%*%Tau2_noncmc)))

##compute m vectors

m_mat12 <-
  matrix(c(as.numeric(colMeans(cbind(0,data_random12_centered[,seq(length(randomcovs12_noncmc))],na.rm=T))),
ncol=1)
m_mat22 <-
  matrix(c(as.numeric(colMeans(cbind(0,data_random12_centered[,c(length(randomcovs12_noncmc)+seq(length(rand
omcovs12_noncmc))],na.rm=T))),ncol=1)
m_mat32 <-
  matrix(c(as.numeric(colMeans(cbind(1,data_random12_centered[,c(2*length(randomcovs12_noncmc)+seq(length(ra
ndomcovs12_noncmc))],na.rm=T))),ncol=1)

##compute variance explained by m

m2 <-
  (t(m_mat12)%*%Tau2_noncmc%*%m_mat12+t(m_mat22)%*%Tau2_noncmc%*%m_mat22+t(m_mat32)%*%Ta
u2_noncmc%*%m_mat32)
}else{
  v12 <- v22 <- v32 <- 0
}

```

```

m2 <- Tau2_noncmc[1,1]
}

if(is.null(randomcovsl3_noncmc)==F){

##compute Sigmas
Sigma13 <- var(cbind(0,data_randoml3_centered[,seq(length(randomcovsl3_noncmc))],na.rm=T)
Sigma23 <-
  var(cbind(0,data_randoml3_centered[,c(length(randomcovsl3_noncmc)+seq(length(randomcovsl3_noncmc))],na.r
    m=T)
Sigma33 <-
  var(cbind(0,data_randoml3_centered[,c(2*length(randomcovsl3_noncmc)+seq(length(randomcovsl3_noncmc))],n
    a.rm=T)

##compute variance explained by vs
v13<- as.numeric(sum(diag(Sigma13%%Tau3_noncmc)))
v23<- as.numeric(sum(diag(Sigma23%%Tau3_noncmc)))
v33<- as.numeric(sum(diag(Sigma33%%Tau3_noncmc)))

##compute m vectors
m_mat13 <-
  matrix(c(as.numeric(colMeans(cbind(0,data_randoml3_centered[,seq(length(randomcovsl3_noncmc))],na.rm=T))),
    ncol=1)
m_mat23 <-
  matrix(c(as.numeric(colMeans(cbind(0,data_randoml3_centered[,c(length(randomcovsl3_noncmc)+seq(length(rand
    omcovsl3_noncmc))],na.rm=T))),ncol=1)
m_mat33 <-
  matrix(c(as.numeric(colMeans(cbind(1,data_randoml3_centered[,c(2*length(randomcovsl3_noncmc)+seq(length(ra
    ndomcovsl3_noncmc))],na.rm=T))),ncol=1)

##compute variance explained by m
m3 <-
  ((m_mat13)%%Tau3_noncmc%%m_mat13+(m_mat23)%%Tau3_noncmc%%m_mat23+(m_mat33)%%Ta
    u3_noncmc%%m_mat33)

}else{
  v13 <- v23 <- v33 <- 0
  m3 <- Tau3_noncmc[1,1]
}

##compute R2 measures

totvar <- sum(f1,f2,f3,v12,v13,v22,v23,v32,v33,m2,m3,sigma2)
l1var <- sum(f1,v12,v13,sigma2)
l2var <- sum(f2,v22,v23,m2)
l3var <- sum(f3,v32,v33,m3)

R2_f1_t <- f1/totvar
R2_f2_t <- f2/totvar
R2_f3_t <- f3/totvar
R2_v12_t <- v12/totvar
R2_v13_t <- v13/totvar
R2_v22_t <- v22/totvar
R2_v23_t <- v23/totvar
R2_v32_t <- v32/totvar
R2_v33_t <- v33/totvar
R2_m2_t <- m2/totvar
R2_m3_t <- m3/totvar

R2_f1_1 <- f1/l1var
R2_f2_2 <- f2/l2var
R2_f3_3 <- f3/l3var

```

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R2_v12_1 <- v12/11var
R2_v13_1 <- v13/11var
R2_v22_2 <- v22/12var
R2_v23_2 <- v23/12var
R2_v32_3 <- v32/13var
R2_v33_3 <- v33/13var
R2_m2_2 <- m2/12var
R2_m3_3 <- m3/13var

##create table of measures

R2_table <-
  matrix(c(R2_f1_t,R2_f2_t,R2_f3_t,R2_v12_t,R2_v13_t,R2_v22_t,R2_v23_t,R2_v32_t,R2_v33_t,R2_m2_t,R2_m3
    _t,
    R2_f1_1,"NA","NA",R2_v12_1,R2_v13_1,"NA","NA","NA","NA","NA","NA",
    "NA",R2_f2_2,"NA","NA","NA",R2_v22_2,R2_v23_2,"NA","NA",R2_m2_2,"NA",
    "NA","NA",R2_f3_3,"NA","NA","NA","NA",R2_v32_3,R2_v33_3,"NA",R2_m3_3)
    ,ncol=4)
rownames(R2_table) <- c("f1","f2","f3","v12","v13","v22","v23","v32","v33","m2","m3")
colnames(R2_table) <- c("total","11","12","13")

##barchart

contributions_stacked <-
  matrix(c(R2_f1_t,R2_f2_t,R2_f3_t,R2_v12_t,R2_v13_t,R2_v22_t,R2_v23_t,R2_v32_t,R2_v33_t,R2_m2_t,R2_m3
    _t,sigma2/totvar,
    R2_f1_1,0,0,R2_v12_1,R2_v13_1,0,0,0,0,0,sigma2/11var,
    0,R2_f2_2,0,0,0,R2_v22_2,R2_v23_2,0,0,R2_m2_2,0,0,
    0,0,R2_f3_3,0,0,0,0,R2_v32_3,R2_v33_3,0,R2_m3_3,0),nrow=12,ncol=4)
colnames(contributions_stacked) <- c("total","level-1","level-2","level-3")
rownames(contributions_stacked) <- c("f1","f2","f3",
  "v12","v13","v22","v23","v32","v33",
  "m2","m3","resid")

barplot(contributions_stacked, main="Decomposition", horiz=FALSE,
  ylim=c(0,1),col=c("darkred","steelblue","darkgoldenrod1","darkred","darkred","midnightblue","midnightblue",
  "darkgoldenrod1","darkgoldenrod1","midnightblue","darkgoldenrod1","white"),
  ylab="proportion of variance",
  density=c(NA,NA,NA,20,40,40,20,40,20,40,20,NA),angle=c(0,0,0,45,45,90,135,90,90,135,0,0))

  legend(4.89,.7,title="source",legend=rownames(contributions_stacked),fill=c("darkred","steelblue","darkgoldenrod
  1","darkred","darkred","midnightblue","midnightblue",
  "darkgoldenrod1","darkgoldenrod1","midnightblue","darkgoldenrod1","white"),
  cex=.7, pt.cex =
  1,xpd=TRUE,density=c(NA,NA,NA,30,50,50,30,50,30,50,30,NA),angle=c(0,0,0,45,45,90,135,90,90,135,0,0))

Output <- list(noquote(R2_table))
names(Output) <- c("R2s")
}

return(Output)
}

```



### Online Appendix E: Walkthrough of empirical example predicting math achievement for students nested within teachers nested within schools

Online Appendix E provides a step-by-step demonstration of how to implement the  $R^2$  framework using our empirical example in which we predict student math achievement from student-level, teacher-level, and school-level predictors. Specifically, we walk through how to (1) download the dataset; (2) read the dataset in R; (3) center the dataset and compute cluster means; (4) fit the model in R using *lmer*; and (5) compute all  $R^2$  measures using the model output and the *r2mlm3* function.

#### Step 1. Download data at <https://www.stata-press.com/data/mlmus2.html>

This link contains the support materials for Multilevel and Longitudinal Modeling Using Stata, Second Edition (Rabe-Hesketh & Skrondal, 2005). At this website, there will be a link to a zip file titled “mlmus2.zip.” After clicking this and downloading it, the appropriate dataset will be a DTA file in the zip folder titled “instruction.dta”.

#### Step 2. Read in data

This data can be read using the *read.dta* function in the *foreign* package. See below for R code.

```
##install package, if not already installed
install.packages("foreign")

##load foreign package
library(foreign)

##read in data, here naming the dataset "instruction"
#replace ~ with the actual file path
instruction <- read.dta("~/instruction.dta")
```

#### Step 3. Center data and compute cluster means

In our analysis, we cluster-mean-centered each level-1 predictor and each level-2 predictor using the method described in the manuscript. We additionally included cluster-means of level-1 variables and level-2 variables. This can be accomplished using the following R code:

```
##create version of dataset to be centered
instruction_centered <- instruction

##create temporary version of dataset (used in computing means below)
instruction_centered_temp <- instruction

##loop through level-2 units (classrooms)
for(clus2 in seq(max(instruction_centered[, "classid"]))) {

##loop through observations
  for(i in seq(nrow(instruction_centered))) {

##determine if observation belongs to the current level-2 unit
```

```

if(instruction_centered[i,"classid"]==clus2){

##center each level-1 predictor by classroom mean
  instruction_centered[i,"mathkind"] <- instruction_centered[i,"mathkind"]-
  mean(instruction_centered_temp[which(instruction_centered_temp[, "classid"]==clus2),"mathkind"],na.rm=T)
  instruction_centered[i,"girl"] <- instruction_centered[i,"girl"]-
  mean(instruction_centered_temp[which(instruction_centered_temp[, "classid"]==clus2),"girl"],na.rm=T)
  instruction_centered[i,"ses"] <- instruction_centered[i,"ses"]-
  mean(instruction_centered_temp[which(instruction_centered_temp[, "classid"]==clus2),"ses"],na.rm=T)

}
}
}

##loop through level-3 units (schools)
for(clus3 in seq(max(instruction_centered[, "schoolid"]))) {

##loop through observations
for(i in seq(nrow(instruction_centered))) {

##determine if observation belongs to the current level-3 unit
  if(instruction_centered[i,"schoolid"]==clus3){

##school-mean center each level-2 predictor
    instruction_centered[i,"mathprep"] <- instruction_centered[i,"mathprep"]-
    mean(instruction_centered_temp[which(instruction_centered_temp[, "schoolid"]==clus3),"mathprep"],na.rm=T)
    instruction_centered[i,"mathknow"] <- instruction_centered[i,"mathknow"]-
    mean(instruction_centered_temp[which(instruction_centered_temp[, "schoolid"]==clus3),"mathknow"],na.rm=T)
    instruction_centered[i,"yearstea"] <- instruction_centered[i,"yearstea"]-
    mean(instruction_centered_temp[which(instruction_centered_temp[, "schoolid"]==clus3),"yearstea"],na.rm=T)

##compute school-means for each level-1 and level-2 predictor
    instruction_centered[i,"mathprep_schmean"] <-
    mean(instruction_centered_temp[which(instruction_centered_temp[, "schoolid"]==clus3),"mathprep"],na.rm=T)
    instruction_centered[i,"mathknow_schmean"] <-
    mean(instruction_centered_temp[which(instruction_centered_temp[, "schoolid"]==clus3),"mathknow"],na.rm=T)
    instruction_centered[i,"mathkind_schmean"] <-
    mean(instruction_centered_temp[which(instruction_centered_temp[, "schoolid"]==clus3),"mathkind"],na.rm=T)
    instruction_centered[i,"girl_schmean"] <-
    mean(instruction_centered_temp[which(instruction_centered_temp[, "schoolid"]==clus3),"girl"],na.rm=T)
    instruction_centered[i,"ses_schmean"] <-
    mean(instruction_centered_temp[which(instruction_centered_temp[, "schoolid"]==clus3),"ses"],na.rm=T)
    instruction_centered[i,"yearstea_schmean"] <-
    mean(instruction_centered_temp[which(instruction_centered_temp[, "schoolid"]==clus3),"yearstea"],na.rm=T)

  }
}
}

#grand-mean-center level-3 predictors
instruction_centered[, "mathprep_schmean"] <- instruction_centered[, "mathprep_schmean"]-
mean(instruction_centered[, "mathprep_schmean"],na.rm=T)
instruction_centered[, "mathknow_schmean"] <- instruction_centered[, "mathknow_schmean"]-
mean(instruction_centered[, "mathknow_schmean"],na.rm=T)

```

```
instruction_centered[, "mathkind_schmean"] <- instruction_centered[, "mathkind_schmean"] -
mean(instruction_centered[, "mathkind_schmean"], na.rm=T)
instruction_centered[, "girl_schmean"] <- instruction_centered[, "girl_schmean"] -
mean(instruction_centered[, "girl_schmean"], na.rm=T)
instruction_centered[, "ses_schmean"] <- instruction_centered[, "ses_schmean"] -
mean(instruction_centered[, "ses_schmean"], na.rm=T)
instruction_centered[, "yearstea_schmean"] <- instruction_centered[, "yearstea_schmean"] -
mean(instruction_centered[, "yearstea_schmean"], na.rm=T)
```

#### Step 4. Fit model in lmer

This model can be fit using the *lmer* function in the *lme4* package:

```
##install packages, if not already installed
install.packages("lme4")
install.packages("lmerTest")

##load packages
library(lme4)
library(lmerTest)

##fit model
fit_mathgain <- lmer(mathgain ~ mathkind + girl + ses +
  mathprep + mathknow + yearstea +
  mathkind_schmean + girl_schmean + ses_schmean + mathprep_schmean + mathknow_schmean + yearstea_schmean +
  (mathkind | schoolid/classid), data = instruction_centered, control = lmerControl(optimizer = "Nelder_Mead"))

##output results
summary(fit_mathgain)
```

The `summary()` function will output the following results:

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: mathgain ~ mathkind + girl + ses + mathprep + mathknow + yearstea + mathkind_schmean + girl_sc
hmean + ses_schmean + mathprep_schmean +
  mathknow_schmean + yearstea_schmean + (mathkind | schoolid/classid)
Data: instruction_centered
Control: lmerControl(optimizer = "Nelder_Mead")

REML criterion at convergence: 10365

Scaled residuals:
  Min    1Q  Median    3Q   Max
-2.9466 -0.6090 -0.0364  0.5634  4.0661

Random effects:
Groups      Name      Variance  Std.Dev.  Corr
classid:schoolid (Intercept) 2.043e+02 14.29467
              mathkind 4.414e-02  0.21010  -0.22
schoolid     (Intercept) 3.623e+01  6.01887
              mathkind 5.302e-03  0.07281  -0.44
Residual                                6.758e+02 25.99570
Number of obs: 1081, groups: classid:schoolid, 285; schoolid, 105

Fixed effects:
```

ONLINE APPENDIX

Online Appendix to accompany Rights & Sterba (In press). R squared measures for multilevel models with three or more levels. *Multivariate Behavioral Research*. DOI: 10.1080/00273171.2021.1985948

|   | Estimate | Std. Error | df        | t value | Pr(> t )     |
|---|----------|------------|-----------|---------|--------------|
| (Intercept)   | 57.76571 | 1.36791    | 92.64551  | 42.229  | < 2e-16 ***  |
| mathkind  | -0.43074 | 0.03281    | 83.34343  | -13.128 | < 2e-16 ***  |
| girl  | -2.11203 | 1.89558    | 754.50922 | -1.114  | 0.265554     |
| ses   | 5.80394  | 1.45095    | 748.37460 | 4.000   | 6.96e-05 *** |
| mathprep  | 1.68821  | 1.57092    | 166.37160 | 1.075   | 0.284082     |
| mathknow  | 5.93540  | 1.72194    | 162.63173 | 3.447   | 0.000722 *** |
| yearstea  | -0.05250 | 0.16777    | 166.48060 | -0.313  | 0.754730     |
| mathkind_schmean  | -0.32474 | 0.06726    | 114.08571 | -4.828  | 4.32e-06 *** |
| girl_schmean  | 2.07370  | 8.43397    | 123.38818 | 0.246   | 0.806188     |
| ses_schmean   | 5.02485  | 4.02446    | 102.71088 | 1.249   | 0.214658     |
| mathprep_schmean  | 2.45981  | 2.28142    | 102.65648 | 1.078   | 0.283474     |
| mathknow_schmean  | -1.40308 | 1.81452    | 110.99929 | -0.773  | 0.441015     |
| yearstea_schmean  | 0.40647  | 0.20773    | 121.69303 | 1.957   | 0.052674 .   |
| ---   |          |            |           |         |              |
| Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 |          |            |           |         |              |

**Step 5.** Enter parameter estimates and data into *r2mlm3* function

The *r2mlm3* function, and descriptions of the input, can be found in Online Appendix C, and we have now also made it available in the *r2mlm* R package on CRAN.

```
##call function
r2mlm3(

##specify dataset
data=instruction_centered,

##specify columns of dataset containing level-1 predictors
l1_covs=c("mathkind","girl","ses"),

##specify columns of dataset containing level-2 predictors
l2_covs=c("mathprep","mathknow","yearstea"),

##specify columns of dataset containing level-3 predictors
l3_covs=c("mathkind_schmean","girl_schmean","ses_schmean","mathprep_schmean","mathknow_schmean","yearstea_schmean"),

##specify columns of dataset containing level-1 predictors whose slope vary across level-2 units
random_covs12=c("mathkind"),

##specify columns of dataset containing level-1 predictors whose slope vary across level-3 units
random_covs13=c("mathkind"),

##specify columns of dataset containing level-2 predictors whose slope vary across level-3 units
#not included in above model
random_covs23=NULL,

##insert fixed component estimates for each level-1 predictor
#(mathkind, girl, and ses in above output)
gamma_1=c(-0.43074,-2.11203,5.80394),

##insert fixed component estimates for each level-2 predictor
```

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```

#(mathprep, mathknow, and yearstea in above output)
gamma_2=c(1.68821,5.93540,-0.05250),

##insert fixed component estimates for each level-3 predictor
#(each predictor ending in “_schmean” in above output)
gamma_3=c(-0.32474,2.07370,5.02485,2.45981,-1.40308,0.40647),

##specify random effects associated with the level-2 random intercept and the level-1 predictor random slopes a
cross level-2 units
#found under “Random effects” in the group labeled “classid:schoolid”
Tau12=matrix(c(14.29467^2,-0.22*0.21010*14.29467,-0.22*0.21010*14.29467,0.21010^2),2,2),

##specify random effects associated with the level-3 random intercept and the level-1 predictor random slopes a
cross level-3 units
#found under “Random effects” in the group labeled “schoolid”
Tau13=matrix(c(6.01887^2,-0.44*0.07281*6.01887,-0.44*0.07281*6.01887,0.07281^2),2,2),

##specify random effects associated with the level-2 predictor random slopes
#not included in above model
Tau23=NULL,

##specify residual variance
#found under “Random effect” in group labeled “Residual”
sigma2=25.99570^2)

```

The *r2mlm3* function will output the following results:

| \$R2s |                     |                     |                   |                   |
|-------|---------------------|---------------------|-------------------|-------------------|
|       | total               | l1                  | l2                | l3                |
| f1    | 0.144035123153756   | 0.194417853603958   | NA                | NA                |
| f2    | 0.0150373994173882  | NA                  | 0.081824772703193 | NA                |
| f3    | 0.0454555673340852  | NA                  | NA                | 0.603091013329324 |
| v12   | 0.0346170944859092  | 0.0467259725308216  | NA                | NA                |
| v13   | 0.00415738812055641 | 0.00561162067487076 | NA                | NA                |
| v23   | 0                   | NA                  | 0                 | NA                |
| m2    | 0.168738233812099   | NA                  | 0.918175227296807 | NA                |
| m3    | 0.0299154236597132  | NA                  | NA                | 0.396908986670676 |

And will also output the following plot:

