DUELING DYADS: REGRESSION VERSUS MLM ANALYSIS WITH A CATEGORICAL PREDICTOR

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A Thesis Submitted to the Graduate Faculty of

WAKE FOREST UNIVERSITY GRADUATE SCHOOL OF ARTS AND SCIENCES

in Partial Fulfillment of the Requirements

for the Degree of

MASTER OF ARTS

Psychology

August 2022

Winston-Salem, North Carolina

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ACKNOWLEDGEMENTS

“Words are the source of misunderstandings”—Antoine de Saint-Exupéry, *Le Petit Prince* (1943).

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LIST OF ABBREVIATIONS

CN: Cluster Number

DV: Dependent Variable

FF: Female-Female sibling

FML: Full Information Maximum Likelihood

ICC: Intraclass Correlation

IV: Independent Variable

ML: Maximum Likelihood

MLM: Multilevel Modeling

MM: Male-Male sibling

MLM0: The multilevel null model

MLMNIN: The multilevel model with the individual gender variable

MLMNTW: The multilevel model with the gender composition variable (two categories)

MLMYIN: The multilevel model with the interaction term and the individual gender variable

MLMYTH: The multilevel model with interaction terms and the gender composition variable (three categories)

MLMYTW: The multilevel model with the interaction term and the gender composition variable (two categories)

OG: Opposite-Gender sibling

REGNTH: The pooled-regression model with the gender composition variable (three categories)

REGNTW: The pooled-regression model with the gender composition variable (two categories)

REGYTH: The pooled-regression model with interaction terms and gender composition variable (three categories)

REGYTW: The pooled-regression model with interaction term and the gender composition variable (two categories)

REML: Maximum Likelihood Method

SG: Same-Gender sibling

ABSTRACT

Dyadic data is widely used in social and behavioral studies. However, specific techniques must be used due to the nonindependence of dyadic data. This study compared multilevel modeling (MLM) and the pooled-regression approach in the dyadic analysis context. Furthermore, within the context of dyadic analysis, the modeling of categorical explanatory variables is understudied despite its usefulness and importance (Yaremych et al., 2022).

This simulation study investigated the effect of sample size (the numbers of dyads), the main effect of the categorical variable on the dependent variable (DV), the interaction effect between the categorical variable and the continuous variable on DV, and the intraclass correlation (ICC) on power and Type I error rate of parameters of each model. The results indicated that overall, MLM showed higher power than the pooled-regression approach. When investigating interactions, the pooled-regression approach is not recommended due to the high Type I error rate. Forcing individual categorical variable into a level-2 variable is also not recommended for MLM. Further implications and limitations were discussed.

Keywords: dyadic analysis, multilevel modeling, pooled-regression approach.

INTRODUCTION

Dyadic data is widely used in social and behavioral studies. Dyadic data refers to paired data, in other words, data from pairs of individuals who are related to each other. Examples include married-couple dyads (Umberson et al., 2018), parental dyads (Woodman, 2014), roommate dyads (e.g., Haeffel & Hames, 2014), parent-child dyads (e.g., Kochanska et al., 2008), cousin dyads (Garrison & Rodgers, 2016), and twin dyads (e.g., Kendler et al., 2013). By analyzing dyadic data, researchers can address research questions regarding interplay or interdependence within the dyads that cannot be answered with individual data. However, conventional statistical methods cannot be applied to analyze dyadic data due to their nonindependence; these data require specific methods that can handle their nonindependence.

Nonindependence is the most central concept in dyadic data. This means that the paired individuals are related rather than independent (Kenny et al., 2006). Dyad members show increased similarity or dissimilarity compared with others in the sample. Thus, the independent observations’ assumption, an essential assumption to conventional statistical methods, including traditional regression analysis, is violated (Du & Wang, 2016).

Ignoring the nonindependence in the data can be problematic. Nonindependence implies that the sample size is not equal to "*effective unique information units”*(Aarts et al., 2014, p. 492). Variance can be biased when nonindependence is overlooked (Ananth et al., 2005; Zeger & Liang, 1992). For example, when the dyad members’ observation is positively (versus negatively) correlated, the variance of the observations would be underestimated (versus overestimated), which results in inaccurate *p*-values as well (Kenny et al., 2006).

Researchers can address the challenges of nonindependence by modeling it, and one way to do so is by using multilevel modeling (MLM) (Du & Wang, 2016; Ledermann & Kenny, 2017). MLM is one of the most widely used methods for analyzing dyadic data (Ledermann & Kenny, 2017). MLM is advantageous in that it allows researchers to investigate different levels of predictors. In addition, regression-based approaches for dyadic data analysis can be used (e.g., the reciprocal standard dyad model; Kenny et al., 2006). Furthermore, it has been suggested that the pool-regression approach may have advantages when the sample size is small (Tambling et al., 2011), or may serve as an alternative to more complex modeling approaches (Garrison et al., under review).

However, to my best knowledge, MLM has not been explicitly compared to the pooled-regression approach in the dyadic context. Furthermore, within the context of dyadic analysis, the modeling of categorical explanatory variables is understudied despite its usefulness and importance (Yaremych et al., 2022). Thus, comparing these models and seeking a better way to address the categorical explanatory variable in a dyadic context is worthy of scholarly attention. Although many options can be used in analyzing dyadic data, this study focuses on a currently popular approach (MLM) and a previously popular approach (regression-based approach). Further, this study pays attention to the categorical explanatory variable in both approaches.

To this end, a simulation study was conducted. First, dyadic data were generated under certain conditions such as the number of dyads (sample size), the main effect of the categorical variable on a dependent variable (DV), the interaction effect between the categorical variable and the continuous variable on the DV, and the intraclass correlation (ICC). Then, I compared model performance by comparing power and Type I error rate under each condition. In addition, this study attempts to seek a better way to address categorical variables in these models. Specifically, this study investigated power and Type I error rate of the models with different categorical variables.

An Introduction to the Multilevel Approach

MLM can be used to analyze data that has a hierarchical or nested structure. Here is a typical 2-level MLM. For example, researchers may try to model family members' health scores, education scores, and total family income. In this case, the health score of a person i in a family j is expressed as Y_{ij}, and education score of a person i in family j can be expressed as X_{ij} and the total family income of a family j can be expressed as Z_j. Total family income is a level-2 variable, and this is shared by family members. For example, the members in the same family have the same total family income.

Let us say that the data have a level-1 explanatory variable X_{ij} at level-1:

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + e_{ij}$$

where $j(j = 1, \dots, J)$ represents clusters and $i\left(i = 1, \dots, n_j\right)$ represents the group members that are nested in the cluster. The residual at the individual level (level 1), e_{ij}, is assumed to follow a normal distribution: e_{ij}~N (0, σ_e^2). β_{0j} is the intercept for cluster *j*, and β_{1j} is the regression slope for cluster *j*. In most cases of multilevel models, the intercept (β_{0j}) and the slope (β_{1j}) coefficients are cluster specific, and these effects can vary from cluster to cluster. So, basically, the level-1 equation says that the health score of the person i in family j is predicted by intercept, error, and their education scores.

Once the level-1 model is defined, the level-2 of the model can be explained. Let us say that Z is the level 2 variable, total family income:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}Z_j + u_{0j},$$
$$\beta_{1j} = \gamma_{10} + \gamma_{11}Z_j + u_{1j}$$

In these equations, β_{0j} is explained as a function of a level 2 variable (Z_j). Specifically, γ_{00} is the fixed effect for β_{0j} and γ_{01} is the fixed effect that denotes the effect of the level 2 variable (Z_j) on the intercept (β_{0j}), and u_{0j} is the random effect for cluster j, meaning the cluster-specific effect on the β_{0j}. Added to that, β_{1j} is explained as a function of the level-2 variable (Z_j) as well. Specifically, γ_{10} is the fixed effect for β_{1j}, and γ_{11} is the fixed effect that denotes the effect of the level 2 variable (Z_j) on the slope (β_{1j}), and u_{1j} is the random effect for cluster j, meaning that the cluster-specific effect on the β_{1j}. In this example, the intercept β_{0j} and slope (β_{1j}) is predicted by intercept, error, and total family income.

In this level-2 model, the residuals are assumed to have a multivariate normal distribution (MVN) with a mean vector of 0:

$$\begin{bmatrix} u_{0j} \\ u_{1j} \end{bmatrix} \sim MVN\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2_{u_0} & \sigma_{u_{10}} \\ \sigma_{u_{10}} & \sigma^2_{u_1} \end{bmatrix}\right)$$

Pooling these equations together:

$$Y_{ij} = \gamma_{00} + \gamma_{01}Z_j + \gamma_{10}X_{ij} + \gamma_{11}X_{ij}Z_j + u_{0j} + u_{1j}X_{ij} + e_{ij}$$

Thus far, the typical level-2 multilevel model with one level-1 variable and one level-2 variable was briefly discussed. In the next section, the discussion will be extended to multilevel models for dyadic data.

A Multilevel Approach for Dyadic Data Analysis

As discussed earlier, in most cases, the intercepts and slopes from the first-step analysis are allowed to vary across the clusters, as shown in the previous section. MLM can be applied to analyze dyadic data. Dyads have a nested structure where each cluster size is two. Thus, using MLM for dyadic data entails additional consideration due to its small cluster size.

Specifically, the slopes must be constrained and considered to be equal across all dyads; only the intercepts for the dyads are allowed to vary (Kenny et al., 2006). This is because, in dyadic analysis, each group size is limited to two, which is not enough cluster size (sample size in the group). Thus, the slopes cannot vary across the dyads (Kenny et al., 2006; Du & Wang, 2016). In other words, the cluster size in dyadic data is too small so the slope to vary from cluster to cluster. The slopes should be fixed effects, meaning that their impacts are not allowed to vary from dyad to dyad because the cluster size is fixed to two (the smallest possible value).

Again, the β_{1j}, the slope of the level-1 model, is not allowed to vary across the dyads, meaning that it is a fixed coefficient. Thus, to apply the multilevel approach for dyadic analysis, the level-1 equation and level-2 equation can be expressed as follows:

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + e_{ij},$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}Z_j + u_{0j},$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}Z_j$$

Combined the equations together:

$$Y_{ij} = \gamma_{00} + \gamma_{01}Z_j + \gamma_{10}X_{ij} + \gamma_{11}X_{ij}Z_j + u_{0j} + e_{ij}$$

The notation of each element is equal to the previous section, except that β_{0j} is not cluster-specific slope anymore.

Thus far, this current section has briefly covered the application of MLM for dyadic data. However, one primary concept in the MLM, the intraclass correlation (ICC), remains to be discussed. Hence, the following section will briefly cover the ICC.

Intraclass Correlation (ICC)

Intraclass correlation (ICC) denotes the proportion of the variance accounted for by the groups in the multilevel approach. In other words, it means the proportion of cluster-level variance to the total variance. It quantifies the extent to which variance in outcome variables can be explained by dyads. For example, when the ICC is 1, the members in dyads have the same score on the outcome measure, suggesting that group members are totally dependent on each other. Similarly, an ICC of 0 indicates that dyads do not account for any variance in the outcome measure at all. In other words, the group members are totally independent of each other. It is worth noting that the ICC tends to be higher when the group size is small[1]. This present study investigates dyadic analysis, so cluster size is two, the smallest value.

The intraclass correlation (ICC), which indicates the proportion of total variance that can be accounted for by group, can be defined using the null model. Specifically, the ICC (*ρ)* can be decomposed as the variance of level-1 errors and level-2 errors in the null model. The level-1 equation and the level-2 equation of the empty model (null model) can be expressed as:

$$Y_{ij} = \beta_{0j} + e_{ij},$$

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

Pooling together:

[1]Because the ICC and cluster size affects the design effect (Hox, 2010).

$$Y_{ij} = \gamma_{00} + u_{0j} + e_{ij}$$

In the above null model, the ICC can be explained as follows:

$$\rho = \frac{\sigma_{u_0}^2}{\sigma_{u_0}^2 + \sigma_e^2}$$

Level-1 variance (σ_e^2) and level-2 variance ($\sigma_{u_0}^2$) were used in the above equation.

Furthermore, in MLM, maximum likelihood (ML) estimation is the most widely used method to estimate parameters. ML estimates are asymptoticly consistent, and asymptotically efficient (Casella & Berger, 2002; Hox 2010), as long as the sample size is sufficient (Maas & Hox, 2004). Restricted maximum likelihood method (REML) is preferred over full ML (FML) in many cases because (1) it provides better estimates of variance components, (2) it performs better when the sample size is small (Peugh, 2010; Raudenbush & Bryk, 2002). However, if the sample size is large enough, the difference between FML and REML is negligible (McNeish & Stapleton, 2016). Although there are more estimation methods for MLM and sample size issues on different levels, a full discussion of these issues lies beyond the scope of this study.

Regression-based Approach for Dyadic Data Analysis

Regression-based approaches can also be used to analyze dyadic data. For example, it has been suggested that Actor-Partner Interdependence Model (APIM) can be done using a pooled-regression approach (Tambling et al., 2011; Kenny et al., 2006; Oka et al., 2015). A pooled-regression method means that two regression equations and results are pooled together in order to get parameters (Kashy & Kenny, 2000; Kenny et al.,; Tambling et al., 2011). The APIM model (Cook & Kenny, 2005; Kenny, 1996) is a widely-used analytic model for dyadic data (Shamali & Østergaard, 2019). Commonly, structural equation modeling or MLM is used for the APIM model, but Tambling and colleagues (2011) also suggest that a pooled-regression approach can also be used for the APIM model (Tambling et al., 2011) under certain conditions, such as when the sample is small. However, this study is not simulation-based study. Indeed, others, such as Oka and colleagues (2015) have used the pooled-regression approach for the APIM model based on Tabling and colleagues (2011)'s recommendation.

The Discordant Kinship Model

One example of a pooled-regression approach to dyadic data is the discordant kinship model. In this model, kin dyads are used. This model extends the broader class of discordant kinship model, including co-twin-control design. The discordant kinship model has drawn scholarly attention because this design can address the genetic and shared environmental effects without having rare or extensive data (e.g., identical twin data, genetic data; Garrison et al., under review) and with less advanced training.

The discordant kinship model, including the co-twin control design, is an "*extension of the matched case-control design*" (Frisell et al., 2012, p. 1). The Discordant kinship model are especially advantageous when the research questions concern intrafamilial effects because it allows researchers to address within-family effects and between-family effects (Hadd & Rodgers, 2017; Garrison & Rodgers, 2016). Kinship pairs share many important factors, such as early environmental or genetic factors. Thus, by comparing siblings, unobserved shared-environmental effects and genetic effects can be controlled, reducing familial confounds.

Based on the reciprocal-standard dyad model (Kenny et al., 2006), Garrison and Rodgers (2016) and Garrison et al. (Under review) proposed the regression-based model for the sibling comparison design.

$$Y_{j\Delta} = \beta_0 + \beta_1\bar{Y}_j + \beta_2\bar{X}_j + \beta_3 X_{j\Delta} + e_{j,}$$

where,

$$Y_{j\Delta} = Y_{j1} - Y_{j2} \; ; \; X_{j\Delta} = X_{j1} - X_{j2}$$

This model uses difference score of IV and mean score of IV to predict the difference score of the DV. By doing so, it can control for the between-family differences, and enable to investigate the within-family differences more clearly (Garrison et al., under review)

The superscript *j* is for the kinship pair. In this model, the difference score of the kinship pair *j* ($Y_{j\Delta}$) is predicted from the mean score of the kinship pair *j* ($\bar{Y}_j$), the mean score of the independent variable of the kinship pair ($\bar{X}_j$), and the difference score of the kinship pair ($X_{j\Delta}$). The sibling member with a higher DV score becomes the 1 in pair *j*. Thus, $Y_{j\Delta}$ will always be non-negative because this model assigns it to be $Y_{j1} > Y_{j2}$. The initial data were undistinguishable dyadic data, meaning that the members in the dyad pair are initially exchangeable—no meaningful variables can differentiate them. However, the member with a higher DV score than their partner is assigned to be S_1 in pair *j*, and the member with a lower DV score becomes S_2 in pair *j*. This makes distinguishable dyadic data, although it was initially indistinguishable. If both individuals in the pair have the same score on the DV, $S_{1,}$ and S_2 are randomly assigned.

For example, imagine this motivating example. Researchers may be interested in the relationship between education and health outcomes. Researchers can also collect sibling data to address between- and within-familial effects. $\bar{Y}_j$ is the mean of health in sibling pair *j*, and $Y_{j\Delta}$ is a difference score of health in sibling pair *j*. $\bar{X}_j$ is education mean in sibling *j*, and $X_{j\Delta}$ is education difference between the members in sibling pair *j*.

$$\text{health difference score}_j = \beta_0 + \beta_1 \text{ health mean}_j + \beta_2 \text{ education mean}_j + \beta_3 \text{ education difference}_j + e_j$$

So, in the above example, the health difference score of sibling pair *j* will be predicted by the health mean score, education mean score, and education difference score of sibling pair *j*, and researchers are especially interested in the significance of β_3 because the research interest lies in whether education was a meaningful predictor of health even when familial effects are considered.

The mean level ($\bar{X}_j$, $\bar{Y}_j$) represents the between-family variance while the relative difference level of the pair ($Y_{j\Delta}, X_{j\Delta}$) reflects the within-family variance (Garrison et al., Under review). The mean level in the model partially controls for genetic effects and fully controls shared-environmental effects (Garrison & Rodgers, 2016). Thus, a significant association between $Y_{j\Delta}$ and $X_{j\Delta}$ reflects "*modest support for causation with caveats*" while non-significant association reflects suggestive evidence that the association between Y and X is "*not directly causal*" and confounded with within-familial effects (Garrison et al., Under review). Let's say that researchers found a significant association between $Y_{j\Delta}$ and $X_{j\Delta}$. This means that the association between the IV and the DV may be casual while controlling for genetic effects (because identical twins share the same genes) and the shared-environmental effects. But if dyads were not identical twins, but just full siblings, they would not share all the same genes (but some of them), so the conclusion would be different— the association between the IV and the DV is causal while controlling for "partial" genetic effects and shared-environmental effects. In other words, interpretation of the results should consider which type of kinship dyads were used in the study. The discordant kinship model proposed by Garrison & Rodgers (2016) and Garrison et al., (under review) can be applied to address any kind of kin, such as monozygotic twins, dizygotic twins, full siblings, half-siblings, cousins, or adoptees.

Given the discordant kinship model proposed by Garrison & Rodgers (2016) and Garrison et al. (under review), the one limitation of this model is that it is not easy to include a categorical variable. This is especially the case when the categorical variable is a mixed variable, where variances exist both within and between dyads, because it is impossible to calculate the difference score and mean score. This point will be discussed further in a later section.

The discordant kinship model uses the pair's difference scores and mean scores to predict the dependent variable's difference score. However, it is impossible to calculate difference scores for categorical variables. Furthermore, categorical variables in multilevel modeling have been understudied (Yaremych et al., 2021). Thus, this current study also investigates a better way to address categorical variables while comparing two approaches.

Therefore, the aims of the current study are (1) to compare the performance of the regression-based model and MLM for dyadic data, using convergence and Type I error rates, and (2) to seek a better way to handle a categorical variable according to certain conditions

Motivating Example

To help with understanding, data were generated based on the following hypothetical research scenario. In this hypothetical scenario, researchers are interested in the effects of education and gender and their interaction on health outcomes (DV). The measures of health and education are continuous, while gender is categorical. Furthermore, in this scenario, researchers collected sibling data because sibling data allow researchers to address between- and within-familial effects in this relationship. To this end, MLM or regression-based approaches can be used.

The Discordant Kinship Model

In this hypothetical research scenario, researchers first collected a dataset that consisted of sibling pairs. Although there are more options for researchers, this current study focuses on MLM and regression-based approaches, especially the discordant kinship model (Garrison & Rodgers, 2016; Garrison et al., under review). As discussed earlier, the discordant kinship model proposed by Garrison & Rodgers (2016) and Garrison et al., (Under review) can be expressed as follows:

$$Y_{j\Delta} = \beta_0 + \beta_1 \bar{Y}_j + \beta_2 \bar{X}_j + \beta_3 X_{j\Delta} + e_j$$

As discussed above, this model mainly uses the mean scores ($\bar{X}_j,\ \bar{Y}_j$) and the difference scores ($X_{j\Delta}$) of the dyads to predict difference scores ($Y_{j\Delta}$). As briefly discussed above, it is difficult to involve a categorical variable that is a mixed-dyad variable because it is impossible to calculate the mean score and difference score of the categorical variable.

According to Garrison et al. (under review), the model that includes gender can be expressed as follows:

$$Y_{j\Delta} = \beta_0 + \beta_1 \bar{Y}_j + \beta_2 \bar{X}_j + \beta_3 X_{j\Delta} + \beta_4 G_{j1} + \beta_5 G_{j2} + e_j$$

G_{j1} represents the gender of the sibling member in sibling pair j with a higher DV score than their pair, and G_{j2} indicates the gender of the member with a lower DV score. It is not an ideal way to address the gender effect. The G_{j1} variable compares when S_1 (the sibling member with a higher DV score) is female versus male. Imagine all combinations that gender variables can create except the missing data: male-male, female-female, male-female, male-female.

Thus, the G_{j1} variable basically compares when the S_1 is male versus female, which means that it compares when the female is S_1 (the more healthy one) in the pair *j* and the male is S_1 (the more healthy one) in the pair—thus, it compares male-male siblings (MM) and male-female siblings (MF) versus female-female siblings (FF) and female-male siblings (FM). Similarly, G_{j2} variable compares when the S_2 (the sibling with a lower DV score than the other) is male versus female. This means that it compares when the member with lower DV scores is female versus male—it compares MM and FM Versus FF and MF. Table1 summarizes these pairings. The possible combinations are FM, MF, MM and FF. What G_1 variable does is compare FM and FF versus MF and MM. The G_{j2} variable compares the MF and FF versus FM and MM. Thus, this method may make meaningful interpretation difficult because it compares groups that collapsed together Table 1 shows the possible gender compositions in the sibling pair.

Table 1

Possible gender compositions in the sibling pair

	Meaning	FM	MF	MM	FF
G_1	The more healthy one's gender in the pair	Female	Male	Male	Female
G_2	The less healthy one's gender in the pair	Male	Female	Male	Female

Note. MM indicates male-male sibling, FF indicates female-female sibling, and OG indicates opposite-gender sibling

Garrison & Rodgers (2016) have investigated the relationship between the age at first intercourse (AFI) and intelligence. Garrison & Rodgers (2016) have examined the gender effects running different models, and they concluded that gender did not matter. Thus, they standardized AFI by gender. However, this method may not be optimal to apply to another research. It is unclear how strong effect of a categorical variable (in this model, gender) is enough to use this method. Furthermore, standardizing by gender does not explicitly address gender effects on the DV.

Alternatively, the gender variable can be coded as a between-dyads variable that has different factors. First, since the discordant kinship model forces indistinguishable dyadic data to be distinguishable dyadic data (as discussed earlier), all possible combinations of gender variables are (1) male-male (MM); (2) female-female (FF); (3) male-female (MF); (4) female-male (FM). However, it is hard to understand why MF and FM are meaningfully different unless there are any specific theoretical reasons for believing that they are different. For example, S_1 (one with higher DV score than the other in the pair) is female in the opposite-gender siblings (OG), there might have been a meaningful difference in difference score in health outcomes, compared to when S_1 is male in OG.

Thus, a meaningful alternative gender variable (between-dyads variable) may have two possible coding schemes. One way to do so is to code the gender-composition variable to have two factors (i.e., same-gender (SG) siblings versus OG). Another way to do so is to code the gender-composition variable to have three factors (i.e., FF, MM, and OG). Furthermore, the model may or may not have an interaction term. Thus, this study will investigate four discordant kinship models. In the later section, MLM models will be introduced. Regarding model naming, the first three characters indicate whether this model is a pooled-regression model (REG) or multilevel model (MLM). The next character indicates whether this model involves interaction terms. “Y” means this model involves interaction term, and “N” implies this model does not include interaction term. The next two characters indicate how gender variable was coded. “ID” means it is an individual gender variable, meaning that it was coded whether the subject is female or male. “TW” means it has a gender composition variable with two categories (OG and SG). “TH” means it has a gender composition variable with three categories (FF, MM, and OG). For the null model, the model name “MLM0” was used.

First, the model can use the gender-composition variable with two categories: SG siblings and OG siblings.

$$Y_{j\Delta} = \beta_0 + \beta_1\bar{Y}_j + \beta_2\bar{X}_j + \beta_3 X_{j\Delta} + \beta_4 G_j + e_j \qquad (REGNTW)$$

In the above equation, G_j, the gender composition (SG sibling vs. OG siblings) of a sibling pair, addressing whether the gender composition of dyads can predict the health difference score of sibling pair significantly. In this model, an additional interaction term can be added to address interaction, as follows.

$$Y_{j\Delta} = \beta_0 + \beta_1\bar{Y}_j + \beta_2\bar{X}_j + \beta_3 X_{j\Delta} + \beta_4 G_j + \beta_5 X_{j\Delta} G_j + e_j \qquad (REGYTW)$$

The term β_5 represents the interaction between gender composition and the difference score of education on the difference score of health. In other words, it represents how the gender composition of siblings differentiates the education differences between siblings on health differences of siblings. To put it differently, the gender composition moderates the relation between education difference and health differences. The gender-composition is a between-dyad variable, so the sibling pair share this component. It detects the interaction between education difference score in the pair and gender composition (OG versus SG).

Furthermore, this also means the difference score of interaction between education and gender composition. For example, in the sibling pair j, education difference score is the difference between education score of sibling 1 (S_1; the one with a higher DV score than other in the pair) and sibling 2 (S_2; the one with a lower DV score than other in the pair) in the sibling pair j. The interaction between education and gender composition of S_1 on health can be expressed as follow:

$$Education_{j1} \times GenderComposition_j$$

Similarly, the interaction between education and gender composition of S_2 on health can be expressed as follow:

$$Education_{j2} \times GenderComposition_j$$

Since the DV is a health difference score in the model, the interaction terms above can also have a difference score. Because gender composition is a between-dyad variable, the difference score of interaction in the sibling pair can be expressed as follow:

$$Education_{\Delta} \times GenderComposition_j$$

This is one way to understand the interaction between gender composition and education difference score.

If the gender variable is forced to be a between-dyad variable, as discussed, it can also be a categorical variable with three categories:1) FF, 2) MM, and 3) OG. In this case, the equation can be expressed as follow.

$$Y_{\Delta j} = \beta_0 + \beta_1 \bar{Y}_j + \beta_2 \bar{X}_j + \beta_3 X_{\Delta j} + \beta_4 G_{1j} + \beta_5 G_{2j} + e_j \qquad (REGNTH)$$

In the above model, the interaction term can be added as follows:

$$Y_{j\Delta} = \beta_0 + \beta_1\bar{Y}_j + \beta_2\bar{X}_j + \beta_3X_{j\Delta} + \beta_4G_{1j} + \beta_5G_{2j} + \beta_6X_{j\Delta}G_{2j} + \beta_7X_{j\Delta}G_{2j} + e_j(REGYTH)$$

The above two equations involve gender composition variables that have three categories: MM, FF, and OG. Because the gender composition has three categories, it entails two categorical variables.

The G_1 and G_2 variable can be dummy coded or effect coded. This makes the interpretation of coefficients different. In this current research, an effect coding scheme is used (Table 2). Table 2 shows the coding variables used in this study when the gender composition variable was coded as FF, MM and OG. Because gender composition variable has three categories, two coding variables are generated. OG group was chosen as a reference group.

Table 2

Effect coding of gender composition variable when the gender composition variable is coded to have three categories

	G_1	G_2
Female-female sibling (FF)	0	1
Male-male sibling (MM)	1	0
Opposite-gender sibling (OG)	-1	-1

The Multilevel Approach

In the multilevel approach, gender can be either a level-1 variable or a level-2 variable as well. Further, each model may, or may not include interaction effects. Thus, this research will investigate seven multilevel models, including the null model.

The null model, again, is as follows:

$$Y_{ij} = \beta_{0j} + e_{ij}$$

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

Pooling together:

$$Y_{ij} = \gamma_{00} + u_{0j} + e_{ij} \qquad (MLM0)$$

First, gender can be a level-1 variable, which is the most intuitive and logical way to consider it. There is no level-2 variable, and the DV is health outcomes. A level-1 model can be expressed as

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \beta_{2j}G_{1j} + \beta_{3j}X_{ij}G_{2j} + e_{ij}$$

A level-2 model can be expressed as

$$\beta_{0\mathrm{j}} = \gamma_{00} + u_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

$$\beta_{2j} = \gamma_{20}$$

Collapsing the level-1 and level-2 equations together, the composite form of the multilevel model can be expressed as

$$Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + \gamma_{20}G_{ij} + u_{0j} + e_{ij} \qquad (MLMNIN)$$

From the above equation, the interaction term can be added. A level-1 model can be expressed as

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \beta_{2j}X_{ij}G_{1j} + \beta_{3j}X_{ij}G_{2j} + e_{ij}$$

A level-2 model can be expressed as

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

$$\beta_{2j} = \gamma_{20}$$

$$\beta_{3j} = \gamma_{30}$$

The combined form of this multilevel model can be expressed as

$$Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + \gamma_{20}G_{ij} + \gamma_{30}X_{ij}G_{ij} + u_{0j} + e_{ij} \qquad (MLMYIN)$$

Yaremych et al. (2022), and Enders & Tofighi (2007) stressed that categorical variables should be centered in MLM just like continuous variables. Added to that, the centering method is determined not by quantitative indicator, but by the substantive research question. For this study, grand mean of variables was 0. For the coding schemes, dummy coding and effect coding can be used. The deep discussion on centering issue is beyond the scope of the current study.

The gender variable can be a between-dyads variable (or level-2 variable) in two ways: 1) same-gender dyads vs. mixed-gender dyads, and 2) female dyads, male dyads, and mixed-gender dyads. Researchers can use effect coding or dummy coding to address the gender variable with two levels or three levels. In the multilevel model, the level-1 predictor would be education (X), and the level-2 predictor would be the gender composition of sibling pair.

When the gender variable is a level-2 variable—addressing gender composition of the siblings--with 2 categories (SG versus OG), the models can be expressed as:

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + e_{ij}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}G_j + u_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

Pooling these models together yield the following composite form of the multilevel model

$$Y_{ij} = \gamma_{00} + \gamma_{01}G_j + \gamma_{10}X_{ij} + u_{0j} + e_{ij} \qquad (MLMNTW)$$

In the above model, the interaction effect can be added. A level-1 model can be expressed as

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + e_{ij}$$

A level-2 model can be expressed as

$$\beta_{0j} = \gamma_{00} + \gamma_{01}G_j + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}G_j$$

Pooling the level-1 and level-2 models together yield the following composite form of the multilevel model

$$Y_{ij} = \gamma_{00} + \gamma_{01}G_j + \gamma_{10}X_{ij} + \gamma_{11}G_jX_{ij} + u_{0j} + e_{ij} \qquad (MLMYTW)$$

However, if the gender composition variable is a level-2 variable with three categories, a different multilevel model can be yielded. A level-1 model can be expressed as

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + e_{ij}$$

A level-2 model can be expressed as

$$\beta_{0j} = \gamma_{00} + \gamma_{01}\mathrm{G}_{1\mathrm{j}} + \gamma_{02}\mathrm{G}_{2\mathrm{j}} + u_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

Pooling these models together yields the following composite multilevel model.

$$Y_{ij} = \gamma_{00} + \gamma_{01}G_{1j} + \gamma_{02}G_{2j} + \gamma_{10}X_{ij} + u_{0j} + e_{ij} \qquad (MLMYTH)$$

In the above equation, the interaction effect can be added. A level-1 model can be expressed as

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + e_{ij}$$

A level-2 model can be expressed as

$$\beta_{0j} = \gamma_{00} + \gamma_{01}\mathrm{G}_{1\mathrm{j}} + \gamma_{02}\mathrm{G}_{2\mathrm{j}} + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}G_{1j} + \gamma_{12}G_{2j}$$

Combining these models together yields the composite multilevel models as follows:

$$Y_{ij} = \gamma_{00} + \gamma_{01}G_{1j} + \gamma_{02}G_{2j} + \gamma_{10}X_{ij} + \gamma_{11}G_{1j}X_{ij} + \gamma_{12}G_{2j}X_{ij} + u_{0j} + e_{ij} \; (MLMYTH)$$

Thus far, seven multilevel models are introduced.

This current research will investigate the regression-based approach and multilevel approach. Thus far, this section briefly covered how a categorical variable can be addressed in both approaches with an example of a hypothetical research scenario. The following section will discuss how this current study can be carried out to answer research questions.

METHOD

Current Study

The key aim of this paper is to compare multilevel models and pooled-regression models when analyzing dyadic data. A further aim is to seek a better way to address categorical variables in the dyadic analysis framework. To this end, a simulation study can answer these questions. Convergence rate, Type I error rate, and power will be used to evaluate model performance.

Simulation Design

To address research questions, dyadic data were generated based on a hypothetical research scenario. In that hypothetical scenario, researchers were interested in the effects of education, gender, and their interaction on health outcomes (DV). Furthermore, in this scenario, researchers collected sibling data because sibling data allow researchers to address between- and within-familial effects in this relationship. In this scenario, MLM or pooled-regression approach can be used.

For data generation, management, and analysis, R (version 4.1.2) was used (R Core Team, 2021), packages such as discord (version 1.1.0.9; Garrison & Trattner, 2021), tidyverse (version 1.3.1;Wickham et al., 2019), lmerTest (version 3.1.3; Kuznetsova, Brockhoff, & Christensen, 2017), apaTables (version 2.0.8; Stanley, 2021) were mainly used. With this generated dataset, this study investigated and compared the multilevel model and the discordant kinship model that Garrison and Rodgers (2016) proposed. The four factors that were manipulated for this study are: 1) sample size, 2) intraclass correlation, 3) the main effect of the categorical variable, and 4) the interaction effect of categorical variable and continuous variable.

Sample Size

Sample size influences estimation. In dyadic analysis, it has been suggested that at least 50 dyads are needed (when there are no singletons) to get a reliable and valid estimation in multilevel modeling (Du & Wang, 2016).

Three separate sample sizes were chosen to address how small, medium, and large sample sizes affect the estimations; 30 dyads (total 60 people), 120 dyads (total 240 people), and 510 dyads (total 1020 people). Du & Wang (2016) included 500 dyads (1000 people) as the largest sample size in their simulation study. I chose these sizes because these dyad numbers are multiples of six. This study involves models with a categorical variable that have two and three factors.

ICC

As discussed in the introduction, ICC influences the estimates. Generally, ICC denotes how much variance can be explained by dyads. As discussed in the introduction, ICC can be calculated from the null model (Hox, 2010).

It is worth noting that as group size gets smaller, ICC tends to be higher (Hox, 2010) in MLM. In Du & Wang (2016), ICC for 0.1, 0.2, 0.3, 0.5, and 0.7 were used to simulate dyadic analysis using MLM. In this work, Du & Wang (2016) found that when ICC is equal to or less than 0.2 ($ICC \leq 0.2$), more convergence issues may occur in dyadic analysis using MLM. Thus, I included 0.2 as a minimum level of ICC because of this finding.

Further, 0.4 and 0.8 of ICC can be found in the literature as well. For example, 0.43 of ICC was observed among opposite-gender sibling pairs in weight (Raskind et al., 2018). Furthermore, ICC sometimes can be over 0.8; 0.8 of ICC is observed in romantic dyads (McIsaac et al., 2008).

Main effect and Interaction effect of Categorical Variable

The main effect of the categorical variable is also included in this study. In this hypothetical scenario, researchers try to predict health outcome (Y) with education (X), Gender (G), and interaction between income and gender (XG) at individual levels.

$$Y = \beta_0 + \beta_1 X + \beta_2 G + \beta_1 XG + e$$

At the within-dyad level, I set the standardized beta coefficient of a categorical variable (gender) to be 0.1, 0.3, and 0.5, as conventional wisdom suggests as small, medium, and large effect size (Cohen, 1992). Furthermore, the value of 0 were included as well. Similarly, I also include 0, 0.1, 0.3, and 0.5 as a beta weight of the interaction term.

Other Settings

I set the continuous IV (education) to have a 0.3 standardized beta weight (moderate association) because research questions in this current study are focused on a categorical variable. Furthermore, I assumed that there are no singletons nor missing data in this simulation study because this issue is not the focus of interest.

Further, it is worth explaining the data generation process. First, this study involves education (continuous variable), gender (categorical variable)—and interaction between these two variables. The impacts on the DV of each IV, the main effects of IVs, are weighted by beta1, beta2, and beta3 in the conditions.

Moreover, education and gender may have within- and between- dyads effects on the DV. Between-dyad effects mean effects that are shared by dyads, which means that it is an identical effect for sibling members within the same dyads. Within-dyad effects mean effects that exist within the dyads. To manipulate the ICC, these within- and between-variances were weighted. The data generation equation is as follows:

$$\begin{aligned} Y_{ij} = \beta_1(&ICCweight_{within}edu_{within} + ICCweight_{btw}edu_{btw}) \\ &+ \beta_2\big(ICCweight_{within}gender_{individual} \\ &+ ICCweight_{btw}gender_{Composition}\big) \\ &+ \beta_3(ICCweight_{within}edu_{within}gender_{individual}) + \mathrm{error}_{btw} \\ &+ \mathrm{error}_{within} \end{aligned}$$

I manipulated the within- and between- variance ratio in education and within-and between variance ratio in gender (individual gender effect and gender composition effect) to be the same. Furthermore, during the data generation process, between effects of gender were manipulated by the same-gender siblings versus mixed-gender siblings' scheme. Moreover, the interaction is at the within-dyads level. The limitation stemming from these points will be discussed in the limitation section. Error variances have a standard normal distribution, mean for 0 and standard deviation for 1. The error between indicates error variance in the between-dyad level. An error within indicates error variance in the within-dyad level. The above equation summarizes how the data in this study were generated. Table 3 summarizes the model information about whether each model contains interaction or not and how each model coded gender variables. Table 4 presents model equations. Table 5 presents which parameters correspond to gender, education, and interaction effects.

Table 3

Model information on interaction and gender variable

Model	Interaction	Gender Variable
REGNTW	No	Two categories: OG and SG
REGNTH	No	Three categories: MM, FF, and OG
REGYTW	Yes	Two categories: OG and SG
REGYTH	Yes	Three categories: MM, FF, and OG
MLM0	No	No gender variable
MLMNIN	No	Two categories: Female and Male
MLMYIN	Yes	Two categories: Female and Male
MLMNTW	No	Two categories: OG and SG
MLMYTW	Yes	Two categories: OG and SG
MLMNTH	No	Three categories: MM, FF, and OG
MLMYTH	Yes	Three categories: MM, FF, and OG

Note. MM indicates male-male sibling, FF indicates female-female sibling, and OG indicates opposite-gender sibling.

Table 4

Summary of Model Equations

Model	Equation
REGNTW	$Y_{j\Delta} = \beta_0 + \beta_1\bar{Y}_j + \beta_2\bar{X}_j + \beta_3 X_{j\Delta} + \beta_4 G_j + e_j$
REGNTH	$Y_{j\Delta} = \beta_0 + \beta_1\bar{Y}_j + \beta_2\bar{X}_j + \beta_3 X_{j\Delta} + \beta_4 G_{1j} + \beta_5 G_{2j} + e_j$
REGYTW	$Y_{j\Delta} = \beta_0 + \beta_1\bar{Y}_j + \beta_2\bar{X}_j + \beta_3 X_{j\Delta} + \beta_4 G_j + \beta_5 X_{j\Delta} G_j + e_j$
REGYTH	$Y_{j\Delta} = \beta_0 + \beta_1\bar{Y}_j + \beta_2\bar{X}_j + \beta_3 X_{j\Delta} + \beta_4 G_{1j} + \beta_5 G_{2j} + \beta_6 X_{j\Delta} G_{2j} + \beta_7 X_{j\Delta} G_{2j} + e_j$
MLM0	$Y_{ij} = \gamma_{00} + u_{0j} + e_{ij}$
MLMNIN	$Y_{ij} = \gamma_{00} + \gamma_{10} X_{ij} + \gamma_{20} G_{ij} + u_{0j} + e_{ij}$
MLMYIN	$Y_{ij} = \gamma_{00} + \gamma_{10} X_{ij} + \gamma_{20} G_{ij} + \gamma_{30} X_{ij} G_{ij} + u_{0j} + e_{ij}$
MLMNTW	$Y_{ij} = \gamma_{00} + \gamma_{01} G_j + \gamma_{10} X_{ij} + u_{0j} + e_{ij}$
MLMYTW	$Y_{ij} = \gamma_{00} + \gamma_{01} G_j + \gamma_{10} X_{ij} + \gamma_{11} G_j X_{ij} + u_{0j} + e_{ij}$
MLMNTH	$Y_{ij} = \gamma_{00} + \gamma_{01} G_{1j} + \gamma_{02} G_{2j} + \gamma_{10} X_{ij} + u_{0j} + e_{ij}$
MLMYTH	$Y_{ij} = \gamma_{00} + \gamma_{01} G_{1j} + \gamma_{02} G_{2j} + \gamma_{10} X_{ij} + \gamma_{11} G_{1j} X_{ij} + \gamma_{12} G_{2j} X_{ij} + u_{0j} + e_{ij}$

Table 5

Model parameters summary

	Education effect	Gender effect	Interaction effect	Not relevant to research interest
Model	beta1	beta2	beta3	
REGNTW	$\beta_3 X_{j\Delta}$	$\beta_4 G_j$		$\beta_0,\ \beta_1 \bar{Y}_j,\ \beta_2 \bar{X}_j,\ e_j$
REGNTH	$\beta_3 X_{j\Delta}$	$\beta_4 G_{1j},\ \beta_5 G_{2j}$		$\beta_0,\ \beta_1 \bar{Y}_j,\ \beta_2 \bar{X}_j,\ e_j$
REGYTW	$\beta_3 X_{j\Delta}$	$\beta_4 G_j$	$\beta_5 X_{j\Delta} G_j$	$\beta_0,\ \beta_1 \bar{Y}_j,\ \beta_2 \bar{X}_j,\ e_j$
REGYTH	$\beta_3 X_{j\Delta}, \beta_3 X_{j\Delta}$	$\beta_4 G_{1j}, \beta_5 G_{2j}$	$\beta_6 X_{j\Delta} G_{2j}, \beta_7 X_{j\Delta} G_{2j}$	$\beta_0, \beta_1 \bar{Y}_j,\ \beta_2 \bar{X}_j,\ e_j$
MLM0				$\gamma_{00}, u_{0j}, e_{ij}$
MLMNIN	$\gamma_{10} X_{ij}$	$\gamma_{20} G_{ij}$		γ_{00}, e_{ij}
MLMYIN	$\gamma_{10} X_{ij}$	$\gamma_{20} G_{ij}$	$\gamma_{30} X_{ij} G_{ij}$	$\gamma_{00},, u_{0j}, e_{ij}$
MLMNTW	$\gamma_{10} X_{ij}$	$\gamma_{01} G_j$		$\gamma_{00}, u_{0j}, e_{ij}$
MLMYTW	$\gamma_{10} X_{ij}$	$\gamma_{01} G_j$	$\gamma_{11} G_j X_{ij}$	$\gamma_{00}, u_{0j}, e_{ij}$
MLMNTH	$\gamma_{10} X_{ij}$	$\gamma_{01} G_{1j}, \gamma_{02} G_{2j}$		$\gamma_{00}, u_{0j}, e_{ij}$
MLMYTH	$\gamma_{10} X_{ij}$	$\gamma_{01} G_{1j}, \gamma_{02} G_{2j}$	$\gamma_{11} G_{1j} X_{ij},\ \ \gamma_{12} G_{2j} X_i$	$\gamma_{00}, u_{0j}, e_{ij}$

Note. beta1, beta2, and beta3 are from data-generation equation. Model indicates the model names.

RESULTS

Data were simulated by varying the main effect of education, the main effect of gender, interaction effect, ICC, and sample size, resulting in 117 conditions. I simulated 1000 datasets for each condition. Then, generated datasets were fit in the regression-based models and multilevel models. Convergence rate, singularity rate, power and Type I error rate were calculated for parameters that are relevant to the research question. Table 5 presents which parameter is related to education effect, gender effect, and interaction effect in the models. To save space, I presented only the selected results from all results.

Convergence Rate

Nonconvergence could be an indication of near zero or negative estimation of a variance parameter during an iterative process (Du & Wang, 2016). Model convergence does not necessarily mean a successful model because nonconvergence could also be affected by the number of fitting iterations, a convergence criterion, and starting parameters (Seedorff, Oleson, & McMurray, 2019), and software packages (McCoach et al., 2018).

This present study identified nonconvergence when *lmer* function within lmerTest package (version 3. 1. 3; Kuznetsova, Brockhoff, & Christensen, 2017) throws nonconvergence warning in a default setting, like how Declercq and colleagues (2022) identified nonconvergence. This function in lmerTest package overloads *lmer* function within lmer4 package (Bates et al., 2015); Kuznetzova et al., 2020). In addition, it also computes components for the evaluation of Satterhwaite's denominator degrees of freedom (Kuznetsova et al., 2020). As lme4 package documentation explains, testing convergence is not simple because it is difficult to evaluate the gradient and the Hessian (Bates et al., 2018, Declercq et al., 2022). This is the reason why *lmer* function throws a convergence warning, rather than an error (Declercq et al., 2022). Although package authors suggest how to troubleshoot convergence warning (Declercq et al., 2022), it is beyond the scope of this study to discuss how to troubleshoot convergence warnings or how to evaluate the gradient and the Hessian to test convergence. It is also beyond the scope of this study to discuss the optimal way to define and evaluate nonconvergence.

The seven multilevel models under each of the 117 conditions showed an acceptable convergence rate, ranging from 99.9% to 100%. It showed an acceptable rate across the conditions in terms of convergence rate.

Singularity rate. Singularity rate is defined as how often multilevel models were singular. Under certain conditions (total 47 conditions), MLMNTH and MLMYTH showed 100% of singularity rate. These models involve gender-composition variable with three categories (OG, MM, and FF). In other words, MLMNTH and MLMYTH under these conditions were all singular fits, which suggests this model has an overfitting problem. MLMNTH and MLMYTH use a gender-composition variable with three categories. Table 6 summarizes the condition information on this. MLMNTW and MLMYTW models also showed higher singularity rates, up to 42.5% and 41.5%, respectively. MLMNTW and MLMYTW involve gender composition variable with two categories (OG and SG). This high singularity rates indicates that these models are unreliable (Scandola & Tidoni, 2022) and thus, not recommendable under the conditions that this study investigated. In other words, under the conditions that this study investigated, forcing gender variable into gender composition variable may harm model reliability, resulting in a singularity issue when using MLM. Appendix 2 presents multiple regression results to predict singularity rate of MLM models with CN, beta2, beta3, and ICC.

Table 6

The conditions where MLMNTH or MLMYTH shows 100% of singularity rate

CN	beta2	beta3	ICC
30	0.3	0	0.2
120	0.5	0.5	0.2
510	0.5	0.5	0.2
510	0.5	0.5	0.4
120	0.5	0.5	0.8
510	0.5	0.5	0.8
120	0.3	0	0.2
510	0.3	0	0.2
120	0.3	0	0.4
510	0.3	0	0.4
30	0.3	0	0.8
120	0.3	0	0.8
510	0.3	0	0.8
30	0.5	0	0.2
120	0.5	0	0.2
510	0.5	0	0.2
30	0.5	0	0.4
120	0.5	0	0.4
510	0.5	0	0.4
30	0.5	0	0.8
120	0.5	0	0.8
510	0.5	0	0.8
120	0.3	0.1	0.2
510	0.3	0.1	0.2
120	0.3	0.1	0.4
510	0.3	0.1	0.4
120	0.3	0.1	0.8
510	0.3	0.1	0.8
30	0.5	0.1	0.2
120	0.5	0.1	0.2
510	0.5	0.1	0.2
30	0.5	0.1	0.4
120	0.5	0.1	0.4
510	0.5	0.1	0.4
30	0.5	0.1	0.8
120	0.5	0.1	0.8
510	0.5	0.1	0.8
510	0.3	0.3	0.2
510	0.3	0.3	0.4
510	0.3	0.3	0.8
120	0.5	0.3	0.2
510	0.5	0.3	0.2
120	0.5	0.3	0.4
510	0.5	0.3	0.4
30	0.5	0.3	0.8
120	0.5	0.3	0.8
510	0.5	0.3	0.8

Note. beta1, beta2, and beta3 are from data-generation equation. CN indicates the cluster numbers.

Type I Error Rate

The Type I error rate was evaluated for all eleven models and under all the conditions. The 0.05 level of significance was used to determine whether each parameter was significant or not. This study evaluated the Type I error rate by calculating the significance rate of parameters when there is no effect—when the corresponding beta parameter in the data generation equation is zero. For example, under the conditions where beta2 is zero, the parameters that correspond to the (gender effect) beta2 should not be significant. See table 5 for information on which parameters in the models correspond to which effects. A reasonable Type I error rate range is between 2.5% and 7.5% (Bradley, 1978).

Type I error rate of gender effect. The variables that correspond to gender effect have acceptable Type I error rate, ranging from 2.5% to 7.5%. Specifically, Type I error rate of gender effect ranges from 2.7% to 6.4%. To sum up, regarding Type I error rate of gender effect, pooled-regression models and multilevel models showed acceptable Type I error rate. See Appendix 1 for more information on Type I error rate of gender effects.

Type I error rate of the interaction effect. The Type I error rate for this interaction effect in MLMYIN was acceptable, ranging from 2.5% to 7.5%, but not for REGYTW, REGYTH, MLMYTW, and MLMYTH. Only the MLMYIN model showed good Type I error rate, ranged from 3.5% to 7.0%. Type I error rate that were lower than 2.5% or higher than 7.5% were presented.

REGYTW. REGYTW model showed undesirable Type I error rate of interaction effect (Table 7). Figure 1 shows the relationship between Type I and conditions (CN, ICC, and beta2) in REGYTW. Dashed lines represent 2.5% and 7.5% respectively.

Table 7

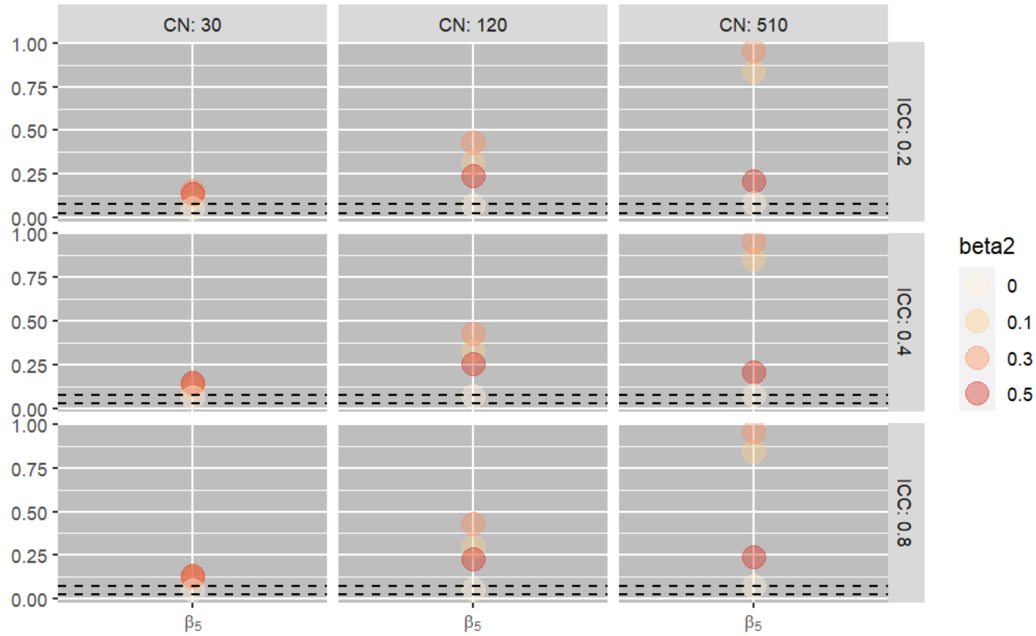
Type I error rate of interaction effect in REGYTW

$\beta_5 X_{j\Delta} G_j$		Condition		
Type 1 error rate (%)	Mean of estimation	CN	ICC	beta2
8.5	0	510	0.2	0
11.1	0.02	30	0.4	0.1
11.3	0.03	30	0.2	0.1
11.9	0.03	30	0.8	0.3
12.4	0.02	30	0.8	0.1
13.3	0.04	30	0.4	0.3
13.4	-0.01	30	0.8	0.5
13.5	-0.01	30	0.2	0.5
14.5	-0.01	30	0.4	0.5
15.3	0.04	30	0.2	0.3
20.8	0	510	0.4	0.5
21.1	0	510	0.2	0.5
22.8	0	120	0.8	0.5
23.8	0	120	0.2	0.5
24	0	510	0.8	0.5
25.4	0	120	0.4	0.5
30	0.02	120	0.8	0.1
32	0.02	120	0.2	0.1
33.5	0.02	120	0.4	0.1
42.9	0.04	120	0.4	0.3
43	0.04	120	0.2	0.3
43.3	0.04	120	0.8	0.3
83.9	0.02	510	0.2	0.1
84.5	0.02	510	0.8	0.1
85.5	0.02	510	0.4	0.1
95.5	0.04	510	0.4	0.3
95.7	0.04	510	0.8	0.3
95.9	0.04	510	0.2	0.3

Note. beta2 denotes beta2 in the data-generation equation. CN indicates the cluster numbers. Type 1 error r ate (%) was rounded to the first digit, and the mean of estimation was rounded to the second digit. 0.00 was noted as 0. Mean of estimation indicates that the mean value of estimation across 1000 datasets.

Figure 1

Type I error rate of interaction in REGYTW



Note. Dashed lines represent 0.025 and 0.075 respectively. CN indicates the cluster numbers.

In REGYTW model, the interaction term, β_5, detects the interaction between education difference score and gender composition (two categories: OG versus SG). This showed unacceptable Type I error rate, even up to 96%. This Type I error rate was high when the sample size was 510, and beta 2 in the data generation equation was 0.3. Multiple regression analysis was conducted to see which factors influences to this result (R^2=0.72, F(7,28) = 10.05, p < .001; Table 8) . The factors, CN, ICC, beta2 in the data generation equation were treated as a factor with the reference groups as zero or the smallest value (for CN, the 30 dyad groups were the reference groups). The regression results are presented in Table 8. The results showed that CN affected the Type I error rate of interaction in REGYTW model. In addition, beta 2 also significantly associated with Type I error rate. Compared to the reference group (where the beta2 is 0), it showed significant difference when the beta2 is 0.1 (*b* = 0.36, $p < .01$) and when beta2 is 0.3 (*b* = 0.44, $p < .01$).

Table 8

Regression results using Type I error rate of interaction effect in REGYTW as the criterion

Predictor	*b* *(estimates)*	*b* 95% CI [LL, UL]	*se*	*t*	Fit
(Intercept)	-0.12	[-0.29, 0.05]	.08	-1.47	
CN					
CN (120)	0.15*	[0.01, 0.30]	.07	2.13	
CN (150)	0.41**	[0.27, 0.56]	.07	5.77	
beta2					
beta2 (0.1)	0.36**	[0.19, 0.53]	.08	4.36	
beta2 (0.3)	0.44**	[0.27, 0.61]	.08	5.33	
beta2 (0.5)	0.13	[-0.04, 0.30]	.08	1.61	
ICC					
ICC (0.4)	0.00	[-0.15, 0.15]	.07	0.02	
ICC (0.8)	-0.00	[-0.15, 0.14]	.07	-0.06	
					R^2 = .715** 95% CI[.40,.77]

Note. A significant *b*-weight indicates the semi-partial correlation is also significant. *b* represents unstandardized regression weights. *se* represents the standard error. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively.
* indicates p < .05. ** indicates p < .01.

REGYTH. Furthermore, REGYTH also showed undesirable Type I error rate (Table 9) up to 25%. Table 9 presents the conditions where Type I error rate of interaction effect in REGYTH were below 2.5% or above 7.5%. Figure 2 shows the relationship between conditions (CN, beta2, and ICC) and Type I error rate of interaction term in REGYTH.

Table 9

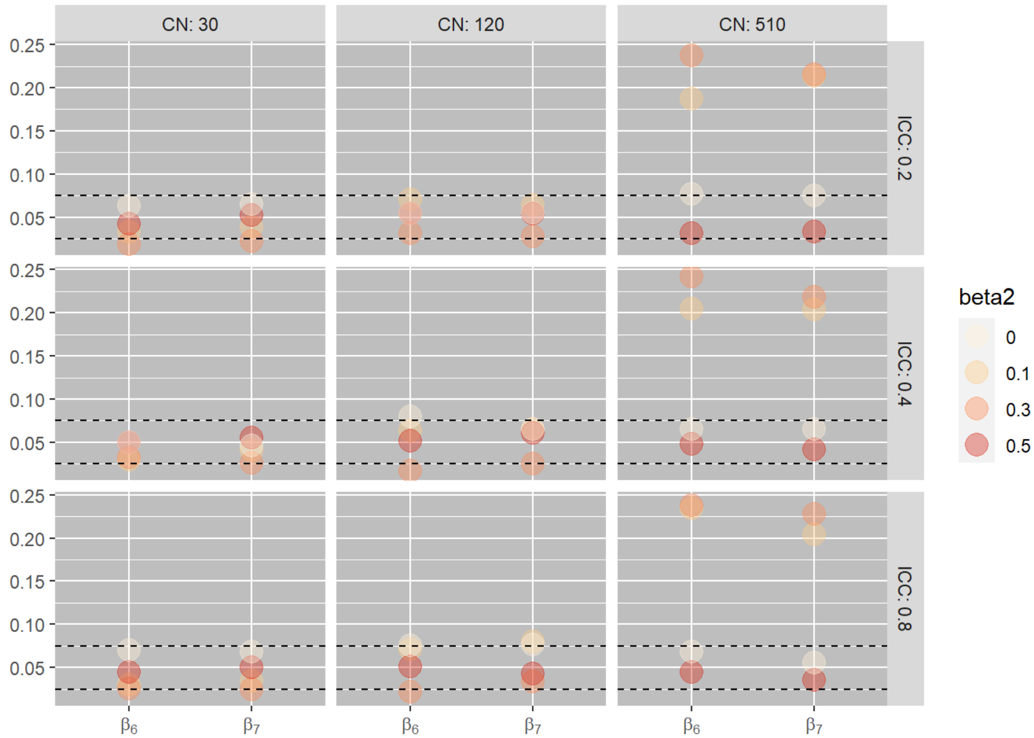
Type I error rate of interaction effect in REGYTH

Type 1 error rate (%)		Mean of estimation		Condition		
$\beta_6 X_{j\Delta} G_{2j}$	$\beta_7 X_{j\Delta} G_{2j}$	$\beta_6 X_{j\Delta} G_{2j}$	$\beta_7 X_{j\Delta} G_{2j}$	CN	beta2	ICC
18.7	21.4	0.02	0.02	510	0.1	0.2
20.5	20.4	0.02	0.02	510	0.1	0.4
7.1	8	0.01	0.02	120	0.1	0.8
23.4	20.4	0.02	0.02	510	0.1	0.8
1.9	2.2	0.03	0.02	30	0.3	0.2
23.7	21.5	0.03	0.03	510	0.3	0.2
1.7	2.5	0.03	0.02	120	0.3	0.4
24.2	21.8	0.03	0.03	510	0.3	0.4
2.6	2.5	0.02	0.02	30	0.3	0.8
2.2	3.4	0.02	0.03	120	0.3	0.8
23.8	22.8	0.03	0.03	510	0.3	0.8
7.7	7.5	0	0	510	0	0.2
8	6.5	0	0	120	0	0.4
7.6	7.7	0	0	120	0	0.8

Note. Beta2 denotes beta2 in the data-generation equation. CN indicates the cluster numbers. Type 1 error rate (%) was rounded to the first digit, and the mean of estimation was rounded to the second digit. 0.00 was noted as 0. Mean of estimation indicates that the mean value of estimation across 1000 datasets

Figure 2

Type I error rate of interaction in REGYTH



Note. Dashed lines represent 0.025 and 0.075 respectively. beta2 denotes beta2 in the data-generation equation. CN indicates the cluster numbers

Multiple regression analysis was conducted to see which factors influenced this result (R^2=.53, F (7, 64) = 10.12, p < .001). Table 9 summarizes the regression results. CN, beta2, ICC were treated as categorical variables. The group with the lowest value for each variable was used as a reference group. When the CN is 510, compared to when the CN is 30, it has a significant difference in this Type I error rate (b = 0.09, p < .001). Compared to the reference group, where beta2 in the data generation equation is 0, it has a significant difference when the beta2 is 0.1 (b = 0.04, p < .05).

Table 10

Regression results using Type I error rate of interaction effect in REGYTH as the criterion

Predictor	*b* (*estimates*)	*b* 95% CI [LL, UL]	*se*	*t*	Fit
(Intercept)	0.03	[-0.00, 0.06]	.02	1.77	
CN					
CN (120)	0.01	[-0.02, 0.04]	.01	0.84	
CN (510)	0.09**	[0.07, 0.12]	.01	6.79	
beta2					
beta2 (0.1)	0.04*	[0.01, 0.07]	.02	2.42	
beta2 (0.3)	0.03	[-0.00, 0.06]	.02	1.78	
beta2 (0.5)	-0.02	[-0.05, 0.01]	.02	-1.15	
ICC					
ICC (0.4)	0.00	[-0.03, 0.03]	.01	0.10	
ICC (0.8)	0.00	[-0.02, 0.03]	.01	0.29	
					R^2 = .525** 95% CI[.29,.61]

Note. A significant *b*-weight indicates the semi-partial correlation is also significant. *b* represents unstandardized regression weights. *se* represents the standard error. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively.
* indicates p < .05. ** indicates p < .01

MLMYTW. In MLMYTW, the interaction term showed Type I error rate above 7.5% (Table 11) but not below 2.5%. Figure 3 represents the relationship between conditions (CN, beta2, and ICC) and Type I error rate of interaction in MLMYTW.

Table 11

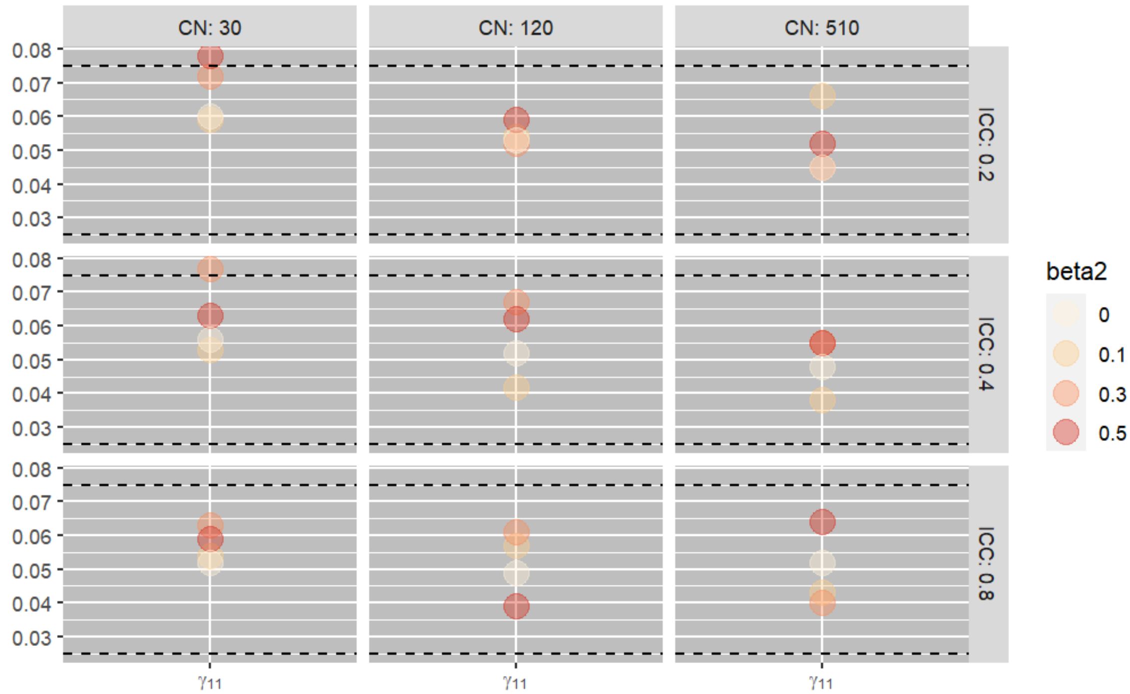
Type I error rate of interaction effect in MLMYTW

Conditions			$\gamma_{11} G_j X_{ij}$	
CN	beta2	ICC	Type I error rate (%)	Mean of estimation
30	0.3	0.4	7.7	0
30	0.5	0.2	7.8	0

Note. beta2 denotes beta2 in the data-generation equation. CN indicates the cluster numbers. Type 1 erro r rate (%) was rounded to the first digit, and the mean of estimation was rounded to the second digit. 0.0 0 was noted as 0. Mean of estimation indicates that the mean value of estimation across 1000 datasets.

Figure 3

Type I error rate of interaction in MLMYTW



Note. Dashed lines represent 0.025 and 0.075 respectively. Beta2 denotes beta2 in the data-generation equation. CN indicates the cluster numbers.

MLMYTH. MLMYTH showed Type I error rate of interaction (Table 12), ranging from 0% to 6.6%. Table 12 presents the cases where Type I error rate of interaction effect in MLMYTH. Although it is not between the range from 2.5% to 7.5%, it was below 2.5% so this has different implication from high Type I error rate (above 7.5%). Figure 4 shows the relationship between conditions and Type I error rate of interaction term in MLMYTH.

Table 12

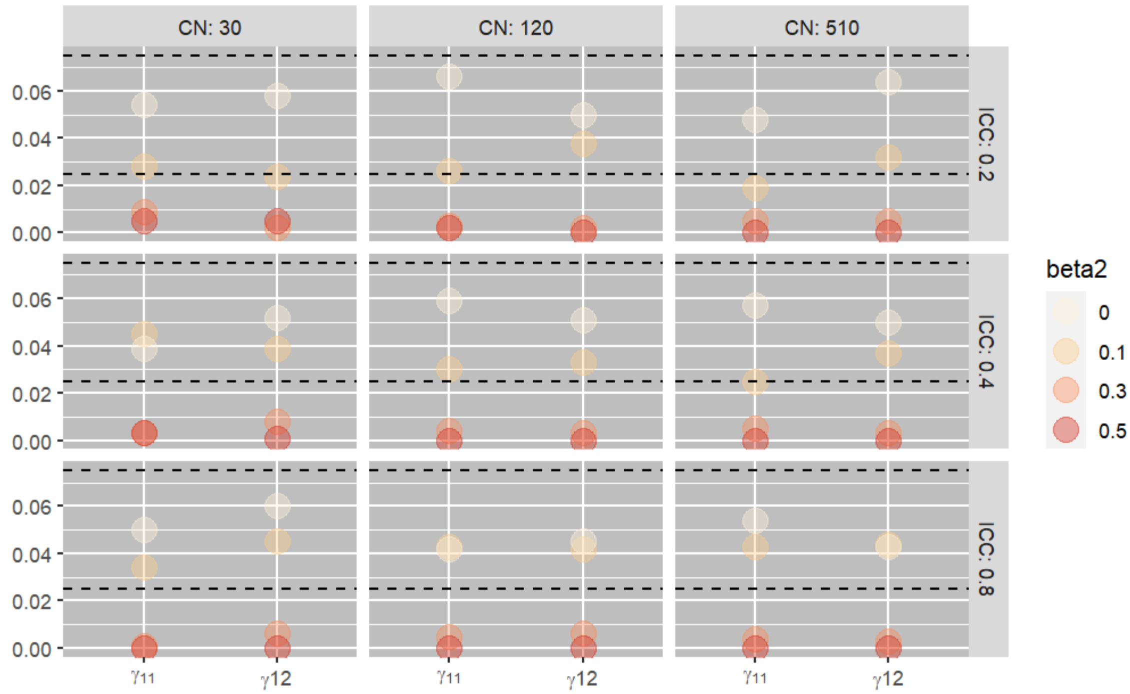
Type I error rate of interaction effect in MLMYTH

Condition			Type I error rate (%)		Mean of estimation	
CN	beta2	ICC	$\gamma_{11}G_{1j}X_{ij}$	$\gamma_{12}G_{2j}X_{ij}$	$\gamma_{11}G_{1j}X_{ij}$	$\gamma_{12}G_{2j}X_{ij}$
30	0.1	0.2	2.8	2.4	0	0
510	0.1	0.2	1.9	3.2	0	0
510	0.1	0.4	2.5	3.7	0	0
30	0.3	0.2	0.9	0.2	0	0
120	0.3	0.2	0.3	0.2	0	0
510	0.3	0.2	0.5	0.5	0	0
30	0.3	0.4	0.3	0.8	0	0
120	0.3	0.4	0.4	0.3	0	0
510	0.3	0.4	0.5	0.3	0	0
30	0.3	0.8	0.1	0.6	0	0
120	0.3	0.8	0.5	0.6	0	0
510	0.3	0.8	0.4	0.3	0	0
30	0.5	0.2	0.5	0.5	0	0
120	0.5	0.2	0.2	0	0	0
510	0.5	0.2	0	0	0	0
30	0.5	0.4	0.3	0.1	0	0
120	0.5	0.4	0	0	0	0
510	0.5	0.4	0	0	0	0
30	0.5	0.8	0	0	0	0
120	0.5	0.8	0	0	0	0
510	0.5	0.8	0	0	0	0

Note. Beta2 denotes beta2 in the data-generation equation. CN indicates the cluster numbers. Type 1 erro r rate (%) was rounded to the first digit, and the mean of estimation was rounded to the second digit. 0.0 0 was noted as 0. Mean of estimation indicates that the mean value of estimation across 1000 datasets

Figure 4

Type I error rate of interaction in MLMYTH



Note. Dashed lines represent 0.025 and 0.075 respectively. The beta2 denotes beta2 in the data-generation equation. CN indicates the cluster numbers.

Multiple regression analysis was conducted to see which factors influenced this result (R^2=.94, F (7,64) = 139.8, p < .001). The predictors, CN, ICC, beta2, were converted into categorical variable. Table 13 presents the regression results. Again, the reference group for each variable was the group with the lowest value. The beta2 significantly affect the Type I error rate of interaction in MLMYTH. Compared to the reference group where beta2 is zero, the conditions with beta for 0.1, 0.3, and 0.5 showed significant differences.

Table 13

Regression results using Type I error rate of interaction effect in MLMYTH as the criterion

Predictor	b	b 95% CI [LL, UL]	se	t	Fit
(Intercept)	0.05**	[0.05, 0.06]	.00	27.15	
CN					
CN (120)	-0.00	[-0.00, 0.00]	.00	-0.52	
CN (510)	-0.00	[-0.00, 0.00]	.00	-0.74	
beta2					
beta2 (0.1)	-0.02**	[-0.02, -0.01]	.00	-9.02	
beta2 (0.3)	-0.05**	[-0.05, -0.04]	.00	-24.77	
beta2 (0.5)	-0.05**	[-0.06, -0.05]	.00	-26.52	
ICC					
ICC (0.4)	0.00	[-0.00, 0.00]	.00	0.05	
ICC (0.8)	0.00	[-0.00, 0.00]	.00	0.62	
					R^2 = .939** 95% CI[.90,.95]

Note. A significant *b*-weight indicates the semi-partial correlation is also significant. *b* represents unstandardized regression weights. *se* represents the standard error. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively.
* indicates p < .05. ** indicates p < .01

Power

In this study, the power of parameters was evaluated by the significance rate of parameters when the effects existed. In other words, the power was operationalized whether a detected effect was present or not based on beta parameter under each condition. The 0.05 level of significance was used to determine whether each parameter was significant or not

In general, the small sample size is related to low power. Moreover, in general, multilevel models seems to have better power for many significant parameters.

Education effect. Education within and education power were estimated. For MLM, education as a level-1 variable was used. For REG models, education difference variables were used to estimate power. Generally, small sample size was related to low power, and MLM showed better performance than REG models. Table 14 summarize the relationship between CN and model on power. Table 15 presents the power of education effect in each model.

Table 14

Power of education effect and cluster number (CN)

CN (Cluster Numbers)	Model	Power (%)
30	REG	81.4%
30	MLM	99.8%
120	REG	99.4%
120	MLM	100%
510	REG	100%
510	MLM	100%

Note. CN indicates the cluster numbers. Model indicates whether the model is MLM models (MLM) or poo led-regression models (REG).

Table 15

Power of education effect in each model

Model	Power (%)
REGNTW	93.9
REGNTH	91.8
REGYTW	93.5
REGYTH	95.2
MLMNIN	99.9
MLMYIN	100
MLMNTW	99.9
MLMYTW	99.8
MLMNTH	100
MLMYTH	100

Note. Model indicates the names of models.

Gender composition effect. To compare the power of gender composition effect, the gender composition variables in eight models were shown in Tables 16 and 17. Table 16 shows that the small sample size was related to the low power, and MLM models tend to perform better than REG models. In table 16, the power of gender composition effect for each model is presented. Furthermore, the MLM models with gender-composition variables with two categories (OG and SG; MLMNTW and MLMYTW) showed better power than MLM models with gender-composition variables with three categories (OG, FF, and MM; MLMNTH and MLMYTH).

Table 16

Power of gender composition effect and cluster number (CN)

CN (Cluster Numbers)	Model	power
30	REG	36.7%
30	MLM	76.1%
120	REG	70.4%
120	MLM	92.5%
510	REG	89.1%
510	MLM	97.3%

Note. CN indicates the cluster numbers. Model indicates whether the model is MLM models (MLM) or poo led-regression models (REG).

Table 17

Power of gender composition effect in models

Model	Power (%)
REGNTW	75%
REGNTH	58.7%
REGYTW	78.1%
REGYTH	61.0%
MLMNTW	94.8%
MLMYTW	94.7%
MLMNTH	85.6%
MLMYTH	85.6%

Note. Model indicates the names of models.

Individual gender effect. To compare the power of gender-within effect (individual gender effect), the power of gender within variables in MLMNIN and MLMYIN models were presented in Table 18. Only MLMNIN and MLMYIN contained individual gender variable (level-1 variable). As Table 18 shows, the small sample size was related to low power. Table 19 presents the power of individual gender effect in MLMNIN and MLMYIN.

Table 18

Power of individual gender effect and cluster number (CN)

CN	Model	Power (%)
30	MLM	91.3%
120	MLM	98.7%
510	MLM	100%

Note. CN indicates the cluster numbers. Model indicates whether the model is MLM models (MLM) or poo led-regression models (REG).

Table 19

Power of individual gender effect in MLMNIN and MLMYIN

Model	Power (%)
MLMNIN	96.1%
MLMYIN	97.2%

Note. Model indicates the names of models

Interaction effect. Power of interaction effect were evaluated. Table 20 shows the power and sample size in REG models and MLM models. Table 21 shows the power of interaction in each model. Again, low sample size was related to low power. Generally, for interaction effect, it is mixed that whether MLM or REG models performed better.

Table 20

Power of interaction effect and cluster number (CN)

CN	Model	Power (%)
30	REG	45.1%
30	MLM	48.2%
120	REG	74.8%
120	MLM	68.8%
510	REG	89.3%
510	MLM	76.2%

Note. CN indicates the cluster numbers. Model indicates whether the model is MLM models (MLM) or poo led-regression models (REG).

Table 21

Power of interaction effect in models

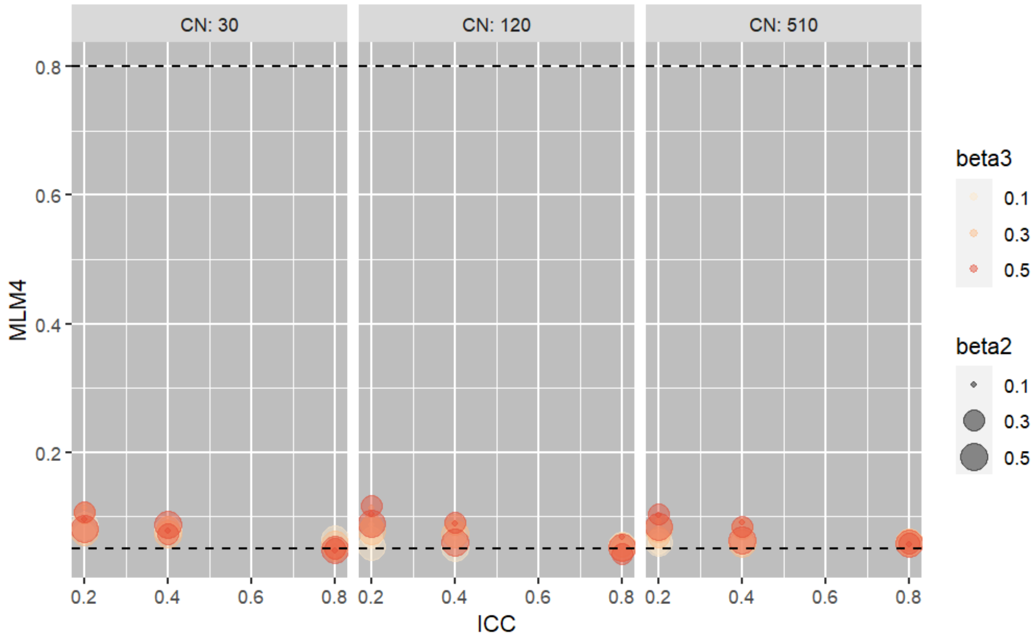
Model	Power (%)
REGYTW	38.5
REGYTH	85.3
MLMYIN	93.2
MLMYTW	7.3
MLMYTH	78.6

Note. Model indicates the names of models

In the MLMYTW model, the interaction term $\gamma_{11} X_{ij} G_j$ detects the cross-level interaction between gender compositions (OG versus SG; level-2 variable) and education variable (level-1 variable). Figure 6 presents the relationship between power and CN. This variable seems to have unacceptably low power ranging from 4.2% to 11.6% Dashed line represents 0.05 and 0.80 respectively. As shown in Figure 5, the power did not exceed 12%.

Figure 5

Power of interaction effect in MLMYTW



Note. Beta2, and beta3 are from the data-generation equation. CN indicates the cluster numbers.

G_2 compared to G_1. In the REGNTH and REGYTH model, G_{1j}, is effect coded variable that compares OG sibling and MM siblings and G_2 is effect-code variable that compares OG and FF. Furthermore, in MLMNTH and MLMYTH model, $\gamma_{01}G_{1j}$ variable is effect coded variable that compares OG and MM, and $\gamma_{02}G_{2j}$ compares OG and FF. Overall, the $\gamma_{01}G_{1j}$ tends to have better power than $\gamma_{02}G_{2j}$ in MLM models, but not in REG models. Table 22 shows this pattern.

Table 22

Two effect-code variables for gender composition variable in models

Parameter	Model	Power (%)
$\beta_4 G_{1j}$	REGNTH	43.4
	REGYTH	64.6
$\beta_5 G_{2j}$	REGNTH	74.0
	REGYTH	57.4
$\gamma_{01} G_{1j}$	MLMNTH	97.2
	MLMYTH	97.2
$\gamma_{02} G_{2j}$	MLMNTH	74.1
	MLMYTH	73.9

Note. Model indicates the names of models.

This result may reflect my data generation process. For example, in G_2, the individual gender effect and gender composition effect are canceled out, resulting in low power. This is because being male is beneficial to health, while being female is detrimental to health. This is individual gender's effect. For between-dyad effect of gender (gender composition effect), being OG sibling is detrimental while being SG sibling is beneficial to health. In G_2, the individual gender's effect and gender composition effect have different direction. The weights have positive valence.

G_{1j} compares OG and MM, while G_{2j} compares OG and FF. In data generation process, being female is detrimental to health, while being FF is beneficial to health. These effects cancel out each other, resulting in the low power of G_{2j}. However, in the regression model, where the DV is not health score, but health difference score, did not show this pattern.

Appendix 3 presents significance rate of parameters in MLM models. Appendix 4 presents significance rate of parameters in pooled-regression models. Significance rate is the rate of this parameters to be significant under the 0.05 level.

DISCUSSION

In this paper, I investigated eleven models and studied the influence of sample size, ICC, and effect size of education, gender, and within-level interactions. I fit these simulated dyadic data and fit this data to both MLM and pooled-regression model and evaluated the convergence rate, Type I error rate, and power. This discussion focuses on parameters that correspond to education, gender, and interaction effect.

Type I Error Rate

Type I error rate of gender effects is in the acceptable range, between 2.5% to 7.5%. For Type I error rate of an interaction effect, only MLMYIN models show reasonable Type I error rate range, among the models that contain interaction term. MLMYIN has an education, individual gender (two categories: Female versus Male), and interaction between education and gender. REGYTW, REGYTH models shows not acceptable Type I error rate of interaction effects. Although, MLMYTW and MLMYTH models showed Type I error rate of interaction effect, it is hard to be considered problematic. The Type I error rate of interaction effect of MLMYTW was 7.7% and 7.8%, which is not that different from 7.5%, and the sample size (CN) was 30, the smallest condition. Furthermore, Type I error rate of interaction effect of MLMYTH was below 2.5%, so it has different implications compared to the high Type I error rate (over 7.5%)

In REGYTW and REGYTH models, the Type I error rate of interaction terms tends to be high when beta2 is 0.3, and the sample size is large (CN = 510). This suggests these interaction terms in these two models detect variance other than within-level interaction. When data were generated, interaction effects were generated within-level—the interaction between education-within effect and gender-within effect. The interaction terms in the REGYTW model, and REGYTH model try to detect the interaction effect between education difference scores and gender composition. As the sample size increases, so does the Type I error rate. This may suggest that these terms detect the variances other than the interaction made in the data generation process. In other words, technically, it might not be the Type I error rate, but detecting the different effects.

The hypothetical advantage of these four models (REGNTH, REGYTH, MLMYTW, and MLMYTH) was that these models were expected to detect interaction effects. It is also worth noting here that only MLMYIN model used gender variable as a level-1 variable (two categories: Female versus Male) while other models use gender composition as a gender variable. To sum up, only MLMYIN model showed Type I error rate of interaction ranging from 2.5% to 7.5% among the models with interaction term (REGNTH, REGYTH, MLMYIN, MLMYTW, and MLMYTH).

To sum up, under the conditions that this study investigated, MLM models showed better power over pooled-regression models overall. However, when using MLM models, it is recommended to use individual gender variable, rather than gender composition variables due to power, Type I error rate, and singularity issues. For pooled-regression models that investigated in this study, it is recommended not to involve interaction terms due to Type I error rate.

Power

A smaller sample size is related to lower power. When the sample size is small, the multilevel models generally showed higher power than pooled-regression models, except for the interaction effect.

Overall, MLM models showed higher power over pooled-regression approach. This may be because, in pooled-regression models, the sample size is the number of dyads, not the number of individual people. In the multilevel design, the effective information unit is not exactly the same as the number of individual people (Hox, 2010), except when the ICC is 0 (but when the ICC is 0, multilevel is no needed); however, it is hardly halved except the case when the ICC is 1 (when the ICC is 1, the multilevel is not useful).

The overall higher power of multilevel models over pooled-regression models shown in this study seems contradictory to Tambling et al. (2011)'s argument; they argued that pooled-regression approach for dyadic analysis is recommendable over multilevel analysis when the sample size is small. However, Tambling et al. (2011)'s pooled-regression equations are not identical to the equations in this study. For example, Tambling et al. (2011)'s model involves the distinguishing variable—the dyads used in their study were hetero-sexual couples, so gender was used as the distinguishing variable.

It is noticeable that the interaction term, γ_{11} in MLMYTW model showed unacceptable low power, ranging from 4.2% to 11.6%, as shown in the results section. The MLMYTW model has an education variable (level 1) and gender-composition variable with two categories (OG versus SG). One of the hypothetical advantages of this model was that γ_{11} in MLMYTW model may detect the interaction between education (level 1) and gender composition (OG versus SG). This is not identical to the interaction made in the data generation process—in the data generation process, interaction is between within-dyad effect of education and individual gender effect—however, it has some overlapped variance. This result shows that the variances that γ_{11} in MLMYTW detects may cancel each other.

Implications for practitioners

One of the aims of this study was to provide practical recommendations on the use of two different approaches and different coding schemes of a categorical variable. Under the conditions this study investigated, overall, MLM showed better power than pooled regression models.

When the model includes interaction term, the pooled-regression models showed a high Type I error rate. Thus, the pooled-regression approach is not recommended when investigating the interaction effect. When the model includes gender composition variable, the MLM models showed problematic results, such as singularity issue. When using MLM models, using an individual gender variable seems to be appropriate rather than using a gender composition variable. Overall, MLM performed better than the pooled-regression approach. However, all these findings are limited to the conditions that this study investigated. For example, this study only investigated the interaction between individual gender and the within-dyad effect of education.

Implications for Methodologists

This study suggests that the pooled-regression approach is not recommended when the research question involves an interaction effect. The interaction effect in pooled-regression models showed a high Type I error rate. Still, technically, this might not be the Type I error rate, but detecting the effects other than interaction effects that were generated through the data generation process (the interaction between individual gender and the within-dyad effect of gender). Especially, the Type I error rates of interaction effect were high when beta2 was 0.3. This might be related to the condition of this study. In this study, beta1 was fixed to 0.3. Future research should be conducted to figure out which effect this model detects.

Limitation

Some of the limitations stem from the scope of this study. First, this study only investigated within-dyad level interaction. Including between-level interaction and cross-level interaction can broaden the scope of the study. It is possible that model performance varies depending on the level of interaction. The models investigated here include parameters that detect cross-level interaction (MLMYTW and MLMYTH), level-1 interaction (MLMYIN), and interaction with gender compositions and education difference scores (REGYTW, REGYTH). So, investigating different levels of interaction with this current model may bring a different perspective. Future research can address different levels of interaction and compare model performance under the conditions.

Second, this study only investigated limited effect sizes, the direction of effects, and the number of groupings. However, different directions of main effects, different number of groupings, and different weights are possible. For example, in this study, the gender composition effect was manipulated as follows: being OG is detrimental to health while being SG is beneficial to health, but there might be a difference between FF, MM, and OG, with different direction of the effects. Because the models in this study have both gender-composition variable with two categories (OG versus SG) and three categories (OG, FF, and MM), this number of groupings may impact the results. Furthermore, in the data generation process, the effect size of between-dyad effects and within-dyad effects was the same across the gender and education variables. However, there might be strong between-dyad effects in education but no between-dyad effects in gender. In future investigations, it is possible to study various conditions with varying effect size or direction of effects.

Another limitation is that the data generation process in this study may favor multilevel approach. Thus, MLM models and pooled-regression models may need to be interpret differently, in that data generation process favors certain approach. This is an important issue for the future study. A further study with different data generation process is therefore recommended to support these findings.

Conclusion

The present study compared pooled-regression approach and multilevel approach in the context of dyadic analysis, especially when the predictor is a categorical variable. The results indicated that (1) MLM showed higher power than the pooled-regression approach overall; (2) pooled-regression model is not recommended when investigating interaction; (3) individual gender variable is recommended for multilevel models and forcing individual gender variable to level-2 variable (using gender-composition variable) is not recommended for multilevel models. Thus, overall, it seems like MLM performs better than pooled-regression models. However, it should be noted that, in this study, the interaction that existed in the dataset were interactions between the within-dyad effect of education and individual gender variable (two categories: Female versus Male)

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APPENDIX 1

Type 1 error rate of gender effects, ICC, CN (cluster numbers) are presented.

Table 23

Type I error rate of the gender effects in each model

	ICC	0.2	0.2	0.2	0.4	0.4	0.4	0.8	0.8	0.8
Model	CN	30	120	510	30	120	510	30	120	510
MLMYTH	$\gamma_{02}G_{2j}$	0.052	0.055	0.052	0.054	0.041	0.049	0.051	0.052	0.043
MLMYTH	$\gamma_{01}G_{1j}$	0.058	0.053	0.044	0.056	0.048	0.047	0.048	0.047	0.041
MLMNTH	$\gamma_{02}G_{2j}$	0.05	0.056	0.05	0.058058	0.043	0.047	0.039	0.051	0.044
MLMNTH	$\gamma_{01}G_{1j}$	0.058	0.053	0.044	0.056056	0.049	0.05	0.039	0.042	0.041
MLMYTW	$\gamma_{01}G_j$	0.043043	0.046	0.049	0.046	0.053	0.056	0.048	0.053	0.056
MLMNTW	$\gamma_{01}G_j$	0.041	0.045	0.047	0.04004	0.052	0.058	0.052	0.052	0.052
MLMYIN	$\gamma_{20}G_{1j}$	0.046	0.054	0.049	0.064	0.053	0.06	0.048	0.05	0.037
MLMNIN	$\gamma_{20}G_{1j}$	0.046	0.054	0.05	0.06006	0.057	0.062	0.051	0.049	0.038
REGYTH	β_5G_{2j}	0.041	0.031	0.043	0.027	0.037	0.046	0.042	0.039	0.028
REGYTH	β_4G_{1j}	0.052	0.031	0.035	0.038	0.04	0.04	0.047	0.048	0.036
REGYTW	β_4G_j	0.031	0.044	0.049	0.03	0.035	0.039	0.028	0.032	0.045
REGNTH	β_5G_{2j}	0.063	0.031	0.058	0.05	0.054	0.056	0.05	0.041	0.03
REGNTH	β_4G_{1j}	0.048	0.057	0.062	0.057	0.059	0.049	0.044	0.048	0.049
REGNTW	β_4G_j	0.041	0.051	0.052	0.055	0.042	0.054	0.037	0.044	0.057

APPENDIX 2

To get a better picture of singularity rate, multiple regression was conducted on singularity rate of MLM models ($R^2 = 0.70$, $F\ (14,804) = 133.8$, $p < .001$). The reference group of gender predictor were no-gender variable group. For example, gender (three categories) variable compares no-gender variable group and groups that uses gender composition with three categories. The reference group of interaction effect predictor were no-interaction group. For other predictors, the lowest-valued group became reference group. For example, beta2 of 0 was reference group of beta2 predictor, and beta3 of 0 was reference group of beta3 predictor, and 30 of CN was reference group of CN predictor.

Table 24

Regression results using singularity rate as the criterion

Predictor	*b* *(estimates)*	*b* 95% CI [LL, UL]	*se*	*t*	Fit
(Intercept)	-0.19**	[-0.25, -0.12]	0.03	-5.62	
Interaction (YES)	-0.02	[-0.05, 0.01]	0.01	-1.40	
Gender (individual)	0.00	[-0.04, 0.05]	0.02	0.14	
Gender (three categories)	0.63**	[0.58, 0.68]	0.02	26.82	
Gender (two categories)	0.21**	[0.16, 0.25]	0.02	8.75	
ICC (0.4)	-0.01	[-0.04, 0.02]	0.02	-0.70	
ICC (0.8)	-0.01	[-0.04, 0.02]	0.02	-0.52	
beta2 (0.1)	0.06*	[0.00, 0.12]	0.03	2.04	
beta2 (0.3)	0.30**	[0.24, 0.36]	0.03	10.00	
beta2 (0.5)	0.35**	[0.29, 0.41]	0.03	11.48	
beta3 (0.1)	0.01	[-0.03, 0.05]	0.02	0.31	
beta3 (0.3)	0.04*	[0.00, 0.08]	0.02	2.09	
Beta3 (0.5)	0.07**	[0.03, 0.11]	0.02	3.23	
CN (120)	-0.04*	[-0.07, -0.00]	0.02	-2.16	
CN (510)	-0.07**	[-0.10, -0.04]	0.02	-4.06	
					R^2 = .700** 95% CI[.66,.72]

Note. A significant *b*-weight indicates the semi-partial correlation is also significant. *b* represents unstandardized regression weights. *se* represents the standard error. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively.
* indicates p < .05. ** indicates p < .01

APPENDIX 3

Significance rate of MLM models is presented below. The 0.05 level of significance was used as criteria. ICC, beta2, and beta3 were conditions. The beta2 and beta3 are from data generation equation. six MLM model names were presented in the second row. All the values were rounded to the second digit.

Table 25

Significance rate of MLM models

			Model name																	
Condition			MLMNIN		MLMYIN			MLMNTW		MLMYTW			MLMNTH			MLMYTH				
ICC	beta2	beta3	$\gamma_{10}X_{ij}$	$\gamma_{20}G_{ij}$	$\gamma_{10}X_{ij}$	$\gamma_{20}G_{ij}$	$\gamma_{30}X_{ij}G_{ij}$	$\gamma_{10}X_{ij}$	$\gamma_{01}G_j$	$\gamma_{10}X_{ij}$	$\gamma_{01}G_j$	$\gamma_{11}G_jX_{ij}$	$\gamma_{10}X_{ij}$	$\gamma_{01}G_{1j}$	$\gamma_{02}G_{2j}$	$\gamma_{10}X_{ij}$	$\gamma_{01}G_{1j}$	$\gamma_{02}G_{2j}$	$\gamma_{11}G_{1j}X_{ij}$	$\gamma_{12}G_{2j}X_{ij}$
0.2	0.1	0	1	1	1	1	0.06	1	0.3	1	0.3	0.06	1	0.93	0.52	1	0.92	0.49	0.03	0.02
0.2	0.1	0	1	1	1	1	0.05	1	0.9	1	0.9	0.05	1	1	0.99	1	1	0.98	0.03	0.04
0.2	0.1	0	1	1	1	1	0.05	1	1	1	1	0.07	1	1	1	1	1	1	0.02	0.03
0.4	0.1	0	1	1	1	1	0.06	1	0.85	1	0.85	0.05	1	0.98	0.25	1	0.98	0.23	0.04	0.04
0.4	0.1	0	1	1	1	1	0.06	1	1	1	1	0.04	1	1	0.75	1	1	0.75	0.03	0.03
0.4	0.1	0	1	1	1	1	0.05	1	1	1	1	0.04	1	1	1	1	1	1	0.03	0.04
0.8	0.1	0	1	1	1	1	0.06	1	1	1	1	0.05	1	1	0.16	1	1	0.13	0.03	0.04
0.8	0.1	0	1	1	1	1	0.06	1	1	1	1	0.06	1	1	0.59	1	1	0.57	0.04	0.04
0.8	0.1	0	1	1	1	1	0.04	1	1	1	1	0.04	1	1	1	1	1	1	0.04	0.04
0.2	0.3	0	1	1	1	1	0.06	1	0.94	1	0.93	0.07	1	1	0.99	1	1	0.99	0.01	0
0.2	0.3	0	1	1	1	1	0.05	1	1	1	1	0.05	1	1	1	1	1	1	0	0
0.2	0.3	0	1	1	1	1	0.04	1	1	1	1	0.04	1	1	1	1	1	1	0	0
0.4	0.3	0	1	1	1	1	0.05	1	1	1	1	0.08	1	1	0.79	1	1	0.75	0	0.01
0.4	0.3	0	1	1	1	1	0.04	1	1	1	1	0.07	1	1	1	1	1	1	0	0
0.4	0.3	0	1	1	1	1	0.04	1	1	1	1	0.06	1	1	1	1	1	1	0	0
0.8	0.3	0	1	1	1	1	0.05	1	1	1	1	0.06	1	1	0.53	1	1	0.44	0	0.01
0.8	0.3	0	1	1	1	1	0.05	1	1	1	1	0.06	1	1	1	1	1	1	0	0.01
0.8	0.3	0	1	1	1	1	0.06	1	1	1	1	0.04	1	1	1	1	1	1	0	0
0.2	0.5	0	1	1	1	1	0.06	0.99	0.99	0.98	0.99	0.08	1	1	1	1	1	1	0	0
0.2	0.5	0	1	1	1	1	0.05	1	1	1	1	0.06	1	1	1	1	1	1	0	0
0.2	0.5	0	1	1	1	1	0.06	1	1	1	1	0.05	1	1	1	1	1	1	0	0
0.4	0.5	0	1	1	1	1	0.05	1	1	0.99	1	0.06	1	1	0.91	1	1	0.88	0	0
0.4	0.5	0	1	1	1	1	0.05	1	1	1	1	0.06	1	1	1	1	1	1	0	0
0.4	0.5	0	1	1	1	1	0.05	1	1	1	1	0.06	1	1	1	1	1	1	0	0
0.8	0.5	0	1	1	1	1	0.05	1	1	1	1	0.06	1	1	0.62	1	1	0.51	0	0
0.8	0.5	0	1	1	1	1	0.05	1	1	1	1	0.04	1	1	1	1	1	1	0	0

0.8	0.5	0	1	1	1	1	0.06	1	1	1	1	0.06	1	1	1	1	1	1	0	0
0.2	0.1	0.1	1	1	1	1	1	1	0.26	1	0.26	0.09	1	0.83	0.36	1	0.86	0.38	0.71	0.68
0.2	0.1	0.1	1	1	1	1	1	1	0.89	1	0.89	0.09	1	1	0.92	1	1	0.95	1	1
0.2	0.1	0.1	1	1	1	1	1	1	1	1	1	0.09	1	1	1	1	1	1	1	1
0.4	0.1	0.1	1	0.99	1	1	0.96	1	0.8	1	0.8	0.08	1	0.94	0.18	1	0.94	0.16	0.61	0.59
0.4	0.1	0.1	1	1	1	1	1	1	1	1	1	0.07	1	1	0.58	1	1	0.59	0.99	0.99
0.4	0.1	0.1	1	1	1	1	1	1	1	1	1	0.07	1	1	1	1	1	0.99	1	1
0.8	0.1	0.1	1	0.98	1	0.99	0.41	1	1	1	1	0.06	1	1	0.18	1	0.99	0.16	0.24	0.24
0.8	0.1	0.1	1	1	1	1	0.95	1	1	1	1	0.05	1	1	0.57	1	1	0.57	0.71	0.7
0.8	0.1	0.1	1	1	1	1	1	1	1	1	1	0.07	1	1	0.99	1	1	1	1	1
0.2	0.3	0.1	1	1	1	1	0.99	1	0.91	1	0.9	0.07	1	1	0.97	1	1	0.97	0.25	0.27
0.2	0.3	0.1	1	1	1	1	1	1	1	1	1	0.07	1	1	1	1	1	1	0.97	0.96
0.2	0.3	0.1	1	1	1	1	1	1	1	1	1	0.06	1	1	1	1	1	1	1	1
0.4	0.3	0.1	1	1	1	1	0.91	1	1	1	1	0.08	1	1	0.7	1	1	0.67	0.18	0.16
0.4	0.3	0.1	1	1	1	1	1	1	1	1	1	0.07	1	1	1	1	1	1	0.86	0.88
0.4	0.3	0.1	1	1	1	1	1	1	1	1	1	0.06	1	1	1	1	1	1	1	1
0.8	0.3	0.1	1	1	1	1	0.38	1	1	1	1	0.05	1	1	0.53	1	1	0.47	0.05	0.06
0.8	0.3	0.1	1	1	1	1	0.92	1	1	1	1	0.05	1	1	1	1	1	1	0.29	0.31
0.8	0.3	0.1	1	1	1	1	1	1	1	1	1	0.06	1	1	1	1	1	1	0.96	0.97
0.2	0.5	0.1	1	1	1	1	0.98	0.99	0.99	0.98	0.99	0.09	1	1	1	1	1	0.99	0.06	0.07
0.2	0.5	0.1	1	1	1	1	1	1	1	1	1	0.05	1	1	1	1	1	1	0.69	0.67
0.2	0.5	0.1	1	1	1	1	1	1	1	1	1	0.06	1	1	1	1	1	1	1	1
0.4	0.5	0.1	1	1	1	1	0.9	1	1	1	1	0.08	1	1	0.88	1	1	0.82	0.04	0.04
0.4	0.5	0.1	1	1	1	1	1	1	1	1	1	0.05	1	1	1	1	1	1	0.46	0.46
0.4	0.5	0.1	1	1	1	1	1	1	1	1	1	0.06	1	1	1	1	1	1	1	1
0.8	0.5	0.1	1	1	1	1	0.4	1	1	1	1	0.06	1	1	0.67	1	1	0.58	0	0
0.8	0.5	0.1	1	1	1	1	0.94	1	1	1	1	0.06	1	1	1	1	1	1	0.05	0.06
0.8	0.5	0.1	1	1	1	1	1	1	1	1	1	0.06	1	1	1	1	1	1	0.72	0.74
0.2	0.1	0.3	1	0.59	1	0.91	1	1	0.2	1	0.2	0.11	1	0.45	0.1	1	0.5	0.12	0.98	0.98
0.2	0.1	0.3	1	1	1	1	1	1	0.78	1	0.78	0.11	1	0.98	0.37	1	1	0.43	1	1
0.2	0.1	0.3	1	1	1	1	1	1	1	1	1	0.09	1	1	0.92	1	1	0.98	1	1
0.4	0.1	0.3	1	0.61	1	0.75	1	1	0.6	1	0.58	0.09	1	0.65	0.06	1	0.61	0.06	0.89	0.89
0.4	0.1	0.3	1	1	1	1	1	1	1	1	1	0.09	1	1	0.11	1	1	0.1	1	1
0.4	0.1	0.3	1	1	1	1	1	1	1	1	1	0.09	1	1	0.32	1	1	0.34	1	1
0.8	0.1	0.3	1	0.5	1	0.53	0.54	1	1	1	1	0.05	1	0.96	0.21	1	0.92	0.19	0.4	0.4
0.8	0.1	0.3	1	0.99	1	0.99	0.98	1	1	1	1	0.05	1	1	0.67	1	1	0.67	0.87	0.88
0.8	0.1	0.3	1	1	1	1	1	1	1	1	1	0.06	1	1	1	1	1	1	1	1
0.2	0.3	0.3	1	1	1	1	1	1	0.82	1	0.8	0.1	1	1	0.63	1	1	0.71	0.91	0.93
0.2	0.3	0.3	1	1	1	1	1	1	1	1	1	0.09	1	1	1	1	1	1	1	1
0.2	0.3	0.3	1	1	1	1	1	1	1	1	1	0.07	1	1	1	1	1	1	1	1
0.4	0.3	0.3	1	1	1	1	1	1	1	1	1	0.08	1	1	0.2	1	1	0.23	0.8	0.81
0.4	0.3	0.3	1	1	1	1	1	1	1	1	1	0.09	1	1	0.76	1	1	0.81	1	1
0.4	0.3	0.3	1	1	1	1	1	1	1	1	1	0.08	1	1	1	1	1	1	1	1
0.8	0.3	0.3	1	1	1	1	0.55	1	1	1	1	0.05	1	1	0.66	1	1	0.62	0.28	0.26

0.8	0.3	0.3	1	1	1	1	0.98	1	1	1	1	0.05	1	1	1	1	1	1	0.83	0.84
0.8	0.3	0.3	1	1	1	1	1	1	1	1	1	0.06	1	1	1	1	1	1	1	1
0.2	0.5	0.3	1	1	1	1	1	0.97	0.97	0.97	0.96	0.08	1	1	0.92	1	1	0.94	0.81	0.81
0.2	0.5	0.3	1	1	1	1	1	1	1	1	1	0.08	1	1	1	1	1	1	1	1
0.2	0.5	0.3	1	1	1	1	1	1	1	1	1	0.08	1	1	1	1	1	1	1	1
0.4	0.5	0.3	1	1	1	1	1	1	1	0.99	1	0.07	1	1	0.46	1	1	0.48	0.6	0.6
0.4	0.5	0.3	1	1	1	1	1	1	1	1	1	0.07	1	1	1	1	1	1	1	1
0.4	0.5	0.3	1	1	1	1	1	1	1	1	1	0.06	1	1	1	1	1	1	1	1
0.8	0.5	0.3	1	1	1	1	0.59	1	1	1	1	0.06	1	1	0.76	1	1	0.7	0.14	0.14
0.8	0.5	0.3	1	1	1	1	1	1	1	1	1	0.05	1	1	1	1	1	1	0.77	0.76
0.8	0.5	0.3	1	1	1	1	1	1	1	1	1	0.06	1	1	1	1	1	1	1	1
0.2	0.1	0.5	1	0.32	1	0.54	1	1	0.21	1	0.21	0.1	1	0.28	0.07	1	0.29	0.05	0.97	0.97
0.2	0.1	0.5	1	0.85	1	0.97	1	1	0.7	1	0.71	0.1	1	0.84	0.1	1	0.89	0.11	1	1
0.2	0.1	0.5	1	1	1	1	1	1	1	1	1	0.1	1	1	0.34	1	1	0.35	1	1
0.4	0.1	0.5	1	0.31	1	0.41	0.99	1	0.52	1	0.51	0.08	1	0.39	0.04	1	0.39	0.05	0.83	0.85
0.4	0.1	0.5	1	0.82	1	0.9	1	1	0.99	1	0.99	0.09	1	0.95	0.04	1	0.95	0.04	1	1
0.4	0.1	0.5	1	1	1	1	1	1	1	1	1	0.09	1	1	0.05	1	1	0.06	1	1
0.8	0.1	0.5	1	0.25	1	0.27	0.37	1	1	1	1	0.05	1	0.84	0.23	1	0.78	0.24	0.27	0.29
0.8	0.1	0.5	1	0.74	1	0.77	0.92	1	1	1	1	0.07	1	1	0.8	1	1	0.8	0.71	0.71
0.8	0.1	0.5	1	1	1	1	1	1	1	1	1	0.06	1	1	1	1	1	1	1	1
0.2	0.3	0.5	0.99	0.99	1	1	1	0.98	0.79	0.98	0.78	0.11	0.99	0.97	0.22	1	0.98	0.25	0.96	0.98
0.2	0.3	0.5	1	1	1	1	1	1	1	1	1	0.12	1	1	0.75	1	1	0.86	1	1
0.2	0.3	0.5	1	1	1	1	1	1	1	1	1	0.1	1	1	1	1	1	1	1	1
0.4	0.3	0.5	1	0.97	1	0.99	0.99	1	1	1	1	0.07	1	0.99	0.05	1	0.99	0.05	0.84	0.84
0.4	0.3	0.5	1	1	1	1	1	1	1	1	1	0.09	1	1	0.13	1	1	0.13	1	1
0.4	0.3	0.5	1	1	1	1	1	1	1	1	1	0.08	1	1	0.41	1	1	0.45	1	1
0.8	0.3	0.5	1	0.92	1	0.92	0.4	1	1	1	1	0.05	1	1	0.78	1	1	0.73	0.26	0.28
0.8	0.3	0.5	1	1	1	1	0.95	1	1	1	1	0.04	1	1	1	1	1	1	0.81	0.78
0.8	0.3	0.5	1	1	1	1	1	1	1	1	1	0.06	1	1	1	1	1	1	1	1
0.2	0.5	0.5	0.97	1	1	1	1	0.93	0.93	0.9	0.93	0.08	0.97	1	0.58	0.98	1	0.67	0.94	0.93
0.2	0.5	0.5	1	1	1	1	1	1	1	1	1	0.09	1	1	1	1	1	1	1	1
0.2	0.5	0.5	1	1	1	1	1	1	1	1	1	0.08	1	1	1	1	1	1	1	1
0.4	0.5	0.5	0.98	1	1	1	0.99	0.99	1	0.98	1	0.09	1	1	0.17	0.99	1	0.16	0.76	0.79
0.4	0.5	0.5	1	1	1	1	1	1	1	1	1	0.06	1	1	0.59	1	1	0.68	1	1
0.4	0.5	0.5	1	1	1	1	1	1	1	1	1	0.06	1	1	1	1	1	1	1	1
0.8	0.5	0.5	0.99	1	0.99	1	0.53	1	1	1	1	0.05	1	1	0.85	1	1	0.81	0.27	0.26
0.8	0.5	0.5	1	1	1	1	0.98	1	1	1	1	0.05	1	1	1	1	1	1	0.85	0.82
0.8	0.5	0.5	1	1	1	1	1	1	1	1	1	0.06	1	1	1	1	1	1	1	1
0.2	0	0	1	0.05	1	0.05	0.06	1	0.04	1	0.04	0.06	1	0.06	0.05	1	0.06	0.05	0.05	0.06
0.2	0	0	1	0.05	1	0.05	0.05	1	0.04	1	0.05	0.05	1	0.05	0.06	1	0.05	0.06	0.07	0.05
0.2	0	0	1	0.05	1	0.05	0.07	1	0.05	1	0.05	0.04	1	0.04	0.05	1	0.04	0.05	0.05	0.06
0.4	0	0	1	0.06	1	0.06	0.06	1	0.04	1	0.05	0.06	1	0.06	0.06	1	0.06	0.05	0.04	0.05
0.4	0	0	1	0.06	1	0.05	0.06	1	0.05	1	0.05	0.05	1	0.05	0.04	1	0.05	0.04	0.06	0.05
0.4	0	0	1	0.06	1	0.06	0.05	1	0.06	1	0.06	0.05	1	0.05	0.05	1	0.05	0.05	0.06	0.05

0.8	0	0	1	0.05	1	0.05	0.06	1	0.05	1	0.05	0.05	1	0.04	0.04	1	0.05	0.05	0.05	0.06
0.8	0	0	1	0.05	1	0.05	0.05	1	0.05	1	0.05	0.05	1	0.04	0.05	1	0.05	0.05	0.04	0.04
0.8	0	0	1	0.04	1	0.04	0.05	1	0.05	1	0.06	0.05	1	0.04	0.04	1	0.04	0.04	0.05	0.04

APPENDIX 4

Significance rate of pooled-regression models are presented below. The 0.05 level of significance was used as criteria. ICC, beta2, and beta3 were conditions. The beta2 and beta3 are from data generation equation. Four pooled-regression model names were presented in the second row. All the values were rounded to the second digit.

Table 26

Significance rate of the pooled-regression models

			Model names														
Condition			REGNTW		REGNTH			REGYTW			REGYTH						
ICC	beta2	beta3	$\beta_3 X_{j_\Delta}$	$\beta_4 G_j$	$\beta_3 X_{j_\Delta}$	$\beta_4 G_{1j}$	$\beta_5 G_{2j}$	$\beta_3 X_{j_\Delta}$	$\beta_4 G_j$	$\beta_5 X_{j_\Delta} G_j$	$\beta_3 X_{j_\Delta}$	$\beta_4 G_{1j}$	$\beta_5 G_{2j}$	$\beta_6 X_{j_\Delta} G_{2j}$	$\beta_7 X_{j_\Delta} G_{2j}$		
0.2	0.1	0	1	0.14	1	0.04	0.04	1	0.16	0.11	0.98	0.03	0.03	0.03	0.04		
0.2	0.1	0	1	0.42	1	0.08	0.09	1	0.66	0.32	1	0.08	0.07	0.07	0.06		
0.2	0.1	0	1	0.96	1	0.27	0.3	1	1	0.84	1	0.43	0.5	0.19	0.21		
0.4	0.1	0	1	0.11	1	0.04	0.04	1	0.14	0.11	0.97	0.03	0.03	0.03	0.04		
0.4	0.1	0	1	0.34	1	0.08	0.07	1	0.59	0.34	1	0.09	0.09	0.06	0.06		
0.4	0.1	0	1	0.92	1	0.21	0.34	1	1	0.86	1	0.37	0.51	0.2	0.2		
0.8	0.1	0	1	0.07	1	0.03	0.04	1	0.1	0.12	0.97	0.03	0.03	0.03	0.04		
0.8	0.1	0	1	0.17	1	0.06	0.07	1	0.37	0.3	1	0.06	0.08	0.07	0.08		
0.8	0.1	0	1	0.6	1	0.16	0.34	1	0.94	0.84	1	0.32	0.49	0.23	0.2		
0.2	0.3	0	0.94	0.88	0.93	0.2	0.32	0.96	0.93	0.15	0.88	0.13	0.2	0.02	0.02		
0.2	0.3	0	1	1	1	0.4	0.73	1	1	0.43	1	0.42	0.71	0.03	0.03		
0.2	0.3	0	1	1	1	0.94	1	1	1	0.96	1	0.98	1	0.24	0.22		
0.4	0.3	0	0.94	0.77	0.94	0.15	0.39	0.96	0.85	0.13	0.88	0.11	0.23	0.03	0.03		
0.4	0.3	0	1	1	1	0.34	0.9	1	1	0.43	1	0.35	0.86	0.02	0.03		
0.4	0.3	0	1	1	1	0.88	1	1	1	0.96	1	0.94	1	0.24	0.22		
0.8	0.3	0	0.95	0.43	0.94	0.1	0.42	0.96	0.47	0.12	0.9	0.09	0.24	0.03	0.03		
0.8	0.3	0	1	0.92	1	0.19	0.91	1	0.99	0.43	1	0.21	0.9	0.02	0.03		
0.8	0.3	0	1	1	1	0.58	1	1	1	0.96	1	0.67	1	0.24	0.23		
0.2	0.5	0	0.96	1	0.96	0.43	0.8	0.96	1	0.14	0.94	0.35	0.69	0.04	0.05		
0.2	0.5	0	1	1	1	0.79	0.99	1	1	0.24	1	0.78	0.98	0.05	0.05		
0.2	0.5	0	1	1	1	1	1	1	1	0.21	1	1	1	0.03	0.03		
0.4	0.5	0	0.98	1	0.97	0.35	0.85	0.98	1	0.14	0.94	0.28	0.77	0.05	0.06		
0.4	0.5	0	1	1	1	0.72	1	1	1	0.25	1	0.71	1	0.05	0.06		
0.4	0.5	0	1	1	1	1	1	1	1	0.21	1	1	1	0.05	0.04		
0.8	0.5	0	0.95	0.89	0.95	0.19	0.87	0.96	0.91	0.13	0.93	0.16	0.8	0.04	0.05		

0.8	0.5	0	1	1	1	0.51	1	1	1	0.23	1	0.48	1	0.05	0.04
0.8	0.5	0	1	1	1	0.93	1	1	1	0.24	1	0.93	1	0.04	0.04
0.2	0.1	0.1	1	0.24	1	0.1	0.36	0.98	0.23	0.15	0.96	0.08	0.02	0.4	0.21
0.2	0.1	0.1	1	0.75	1	0.29	0.97	1	0.86	0.32	1	0.54	0.01	0.98	0.91
0.2	0.1	0.1	1	1	1	0.84	1	1	1	0.8	1	1	0.05	1	1
0.4	0.1	0.1	1	0.29	1	0.06	0.41	0.99	0.3	0.13	0.97	0.1	0.01	0.42	0.23
0.4	0.1	0.1	1	0.9	1	0.2	0.99	1	0.95	0.34	1	0.61	0.02	0.98	0.89
0.4	0.1	0.1	1	1	1	0.66	1	1	1	0.81	1	1	0.11	1	1
0.8	0.1	0.1	1	0.4	0.99	0.05	0.52	0.99	0.43	0.13	0.97	0.12	0.02	0.42	0.18
0.8	0.1	0.1	1	0.96	1	0.07	1	1	0.98	0.33	1	0.63	0.08	0.99	0.9
0.8	0.1	0.1	1	1	1	0.2	1	1	1	0.84	1	1	0.6	1	1
0.2	0.3	0.1	0.93	0.98	0.92	0.21	0.36	0.94	0.99	0.13	0.88	0.39	0.12	0.3	0.16
0.2	0.3	0.1	1	1	1	0.72	0.83	1	1	0.38	1	0.99	0.18	0.96	0.6
0.2	0.3	0.1	1	1	1	1	1	1	1	0.94	1	1	0.52	1	1
0.4	0.3	0.1	0.92	0.98	0.92	0.19	0.5	0.94	0.98	0.15	0.88	0.37	0.13	0.27	0.15
0.4	0.3	0.1	1	1	1	0.72	0.96	1	1	0.4	1	0.99	0.34	0.96	0.6
0.4	0.3	0.1	1	1	1	1	1	1	1	0.95	1	1	0.96	1	1
0.8	0.3	0.1	0.92	0.89	0.9	0.21	0.88	0.94	0.91	0.14	0.88	0.35	0.32	0.29	0.15
0.8	0.3	0.1	1	1	1	0.67	1	1	1	0.42	1	0.95	0.99	0.97	0.56
0.8	0.3	0.1	1	1	1	1	1	1	1	0.96	1	1	1	1	1
0.2	0.5	0.1	0.96	1	0.95	0.33	0.74	0.96	1	0.12	0.94	0.44	0.54	0.29	0.4
0.2	0.5	0.1	1	1	1	0.89	0.95	1	1	0.2	1	0.99	0.76	0.9	0.86
0.2	0.5	0.1	1	1	1	1	1	1	1	0.19	1	1	1	1	1
0.4	0.5	0.1	0.96	1	0.96	0.27	0.81	0.96	1	0.15	0.92	0.36	0.64	0.26	0.4
0.4	0.5	0.1	1	1	1	0.82	1	1	1	0.16	1	0.95	0.92	0.93	0.84
0.4	0.5	0.1	1	1	1	1	1	1	1	0.17	1	1	1	1	1
0.8	0.5	0.1	0.95	0.99	0.94	0.2	0.98	0.95	0.99	0.12	0.92	0.24	0.78	0.25	0.36
0.8	0.5	0.1	1	1	1	0.63	1	1	1	0.18	1	0.79	1	0.93	0.85
0.8	0.5	0.1	1	1	1	1	1	1	1	0.18	1	1	1	1	1
0.2	0.1	0.3	0.87	0.12	0.76	0.29	0.54	0.82	0.12	0.12	0.95	0.15	0.03	0.86	0.85
0.2	0.1	0.3	1	0.42	1	0.79	1	1	0.6	0.3	1	0.9	0.27	1	1
0.2	0.1	0.3	1	0.95	1	1	1	1	1	0.72	1	1	0.99	1	1
0.4	0.1	0.3	0.86	0.15	0.76	0.26	0.58	0.81	0.16	0.13	0.93	0.15	0.03	0.86	0.84
0.4	0.1	0.3	1	0.55	1	0.76	1	1	0.73	0.3	1	0.89	0.36	1	1
0.4	0.1	0.3	1	0.99	1	1	1	1	1	0.75	1	1	0.99	1	1
0.8	0.1	0.3	0.85	0.18	0.72	0.16	0.58	0.79	0.2	0.16	0.93	0.14	0.06	0.85	0.83
0.8	0.1	0.3	1	0.65	1	0.56	1	1	0.76	0.32	1	0.89	0.56	1	1
0.8	0.1	0.3	1	1	1	0.99	1	1	1	0.8	1	1	1	1	1
0.2	0.3	0.3	0.7	0.82	0.66	0.09	0.48	0.67	0.83	0.1	0.86	0.44	0.09	0.78	0.74
0.2	0.3	0.3	1	1	1	0.11	0.99	1	1	0.22	1	1	0.36	1	1
0.2	0.3	0.3	1	1	1	0.22	1	1	1	0.52	1	1	0.96	1	1
0.4	0.3	0.3	0.64	0.84	0.61	0.07	0.63	0.6	0.84	0.12	0.86	0.4	0.12	0.77	0.71
0.4	0.3	0.3	1	1	1	0.14	1	1	1	0.24	1	1	0.69	1	1
0.4	0.3	0.3	1	1	1	0.42	1	1	1	0.57	1	1	1	1	1

0.8	0.3	0.3	0.54	0.76	0.49	0.11	0.78	0.52	0.75	0.1	0.82	0.41	0.3	0.76	0.64
0.8	0.3	0.3	1	1	1	0.27	1	1	1	0.23	1	1	1	1	1
0.8	0.3	0.3	1	1	1	0.8	1	1	1	0.68	1	1	1	1	1
0.2	0.5	0.3	0.74	0.99	0.72	0.23	0.53	0.71	0.99	0.12	0.88	0.46	0.3	0.73	0.76
0.2	0.5	0.3	1	1	1	0.65	0.99	1	1	0.14	1	1	0.68	1	1
0.2	0.5	0.3	1	1	1	1	1	1	1	0.13	1	1	0.99	1	1
0.4	0.5	0.3	0.67	0.98	0.64	0.21	0.72	0.64	0.98	0.08	0.84	0.43	0.34	0.7	0.71
0.4	0.5	0.3	1	1	1	0.65	1	1	1	0.1	1	0.98	0.92	1	1
0.4	0.5	0.3	1	1	1	1	1	1	1	0.11	1	1	1	1	1
0.8	0.5	0.3	0.65	0.88	0.62	0.21	0.84	0.6	0.87	0.09	0.8	0.34	0.57	0.66	0.65
0.8	0.5	0.3	1	1	1	0.63	1	1	1	0.1	1	0.94	1	1	1
0.8	0.5	0.3	1	1	1	1	1	1	1	0.09	1	1	1	1	1
0.2	0.1	0.5	0.77	0.06	0.46	0.11	0.09	0.71	0.06	0.22	0.76	0.1	0.03	0.9	0.82
0.2	0.1	0.5	1	0.05	0.98	0.35	0.41	1	0.1	0.63	1	0.89	0.47	1	1
0.2	0.1	0.5	1	0.07	1	0.93	0.99	1	0.29	0.99	1	1	1	1	1
0.4	0.1	0.5	0.76	0.05	0.45	0.11	0.09	0.72	0.07	0.22	0.72	0.1	0.03	0.88	0.8
0.4	0.1	0.5	1	0.07	0.98	0.36	0.49	1	0.14	0.63	1	0.88	0.48	1	1
0.4	0.1	0.5	1	0.1	1	0.93	0.99	1	0.36	0.99	1	1	1	1	1
0.8	0.1	0.5	0.77	0.07	0.48	0.1	0.11	0.72	0.08	0.24	0.72	0.1	0.04	0.86	0.78
0.8	0.1	0.5	1	0.09	0.98	0.28	0.48	1	0.15	0.64	1	0.87	0.55	1	1
0.8	0.1	0.5	1	0.18	1	0.84	0.99	1	0.42	0.99	1	1	1	1	1
0.2	0.3	0.5	0.6	0.21	0.42	0.05	0.13	0.56	0.23	0.17	0.7	0.25	0.07	0.86	0.76
0.2	0.3	0.5	0.99	0.71	0.97	0.06	0.62	0.99	0.79	0.5	1	0.99	0.56	1	1
0.2	0.3	0.5	1	1	1	0.06	1	1	1	0.95	1	1	1	1	1
0.4	0.3	0.5	0.58	0.23	0.4	0.05	0.16	0.55	0.24	0.18	0.64	0.19	0.05	0.84	0.7
0.4	0.3	0.5	0.99	0.68	0.94	0.06	0.7	0.99	0.75	0.52	1	0.97	0.69	1	1
0.4	0.3	0.5	1	1	1	0.05	1	1	1	0.97	1	1	1	1	1
0.8	0.3	0.5	0.53	0.19	0.38	0.07	0.19	0.5	0.19	0.19	0.6	0.22	0.12	0.82	0.68
0.8	0.3	0.5	0.98	0.61	0.91	0.08	0.79	0.98	0.64	0.55	1	0.95	0.95	1	1
0.8	0.3	0.5	1	1	1	0.15	1	1	1	0.97	1	1	1	1	1
0.2	0.5	0.5	0.45	0.63	0.4	0.11	0.19	0.44	0.63	0.14	0.6	0.35	0.12	0.78	0.7
0.2	0.5	0.5	0.96	1	0.96	0.29	0.76	0.96	1	0.26	1	0.99	0.69	1	1
0.2	0.5	0.5	1	1	1	0.77	1	1	1	0.71	1	1	1	1	1
0.4	0.5	0.5	0.44	0.53	0.4	0.13	0.23	0.42	0.51	0.16	0.55	0.32	0.12	0.75	0.6
0.4	0.5	0.5	0.93	0.98	0.92	0.27	0.89	0.94	0.98	0.28	1	0.98	0.86	1	1
0.4	0.5	0.5	1	1	1	0.8	1	1	1	0.74	1	1	1	1	1
0.8	0.5	0.5	0.39	0.31	0.35	0.1	0.27	0.38	0.27	0.12	0.51	0.24	0.24	0.75	0.58
0.8	0.5	0.5	0.91	0.87	0.86	0.31	0.9	0.92	0.85	0.31	1	0.94	0.99	1	1
0.8	0.5	0.5	1	1	1	0.84	1	1	1	0.8	1	1	1	1	1
0.2	0	0	1	0.04	1	0.05	0.06	1	0.03	0.05	0.99	0.05	0.04	0.06	0.06
0.2	0	0	1	0.05	1	0.06	0.03	1	0.04	0.07	1	0.03	0.03	0.05	0.06
0.2	0	0	1	0.05	1	0.06	0.06	1	0.05	0.09	1	0.04	0.04	0.08	0.07
0.4	0	0	1	0.06	1	0.06	0.05	1	0.03	0.06	0.99	0.04	0.03	0.05	0.05
0.4	0	0	1	0.04	1	0.06	0.05	1	0.04	0.07	1	0.04	0.04	0.08	0.06

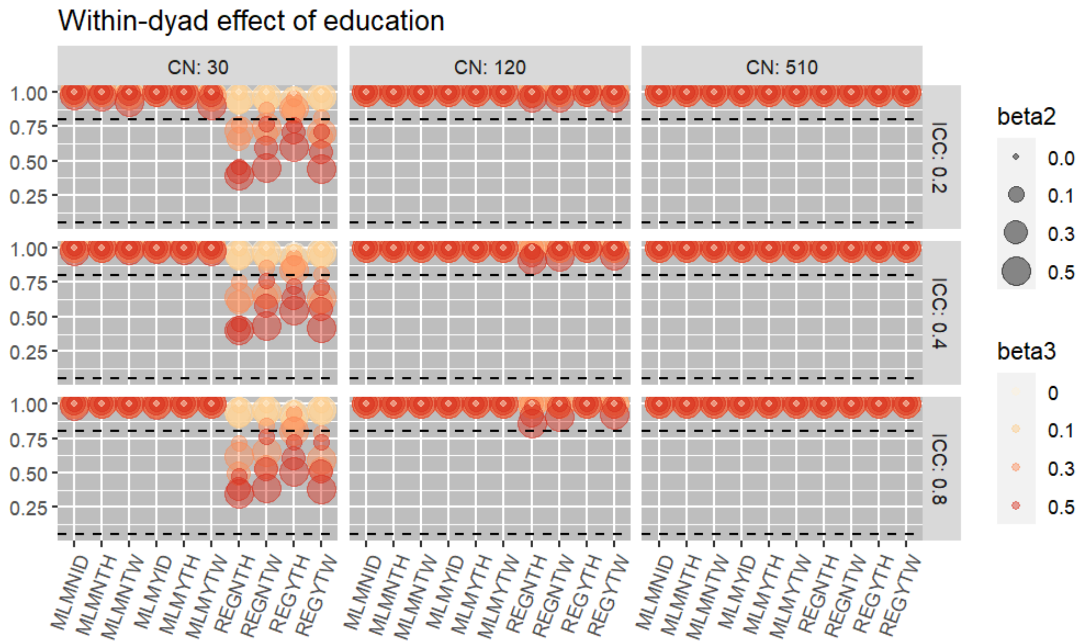
0.4	0	0	1	0.05	1	0.05	0.06	1	0.04	0.07	1	0.04	0.05	0.06	0.06
0.8	0	0	1	0.04	1	0.04	0.05	1	0.03	0.05	0.99	0.05	0.04	0.07	0.07
0.8	0	0	1	0.04	1	0.05	0.04	1	0.03	0.06	1	0.05	0.04	0.08	0.08
0.8	0	0	1	0.06	1	0.05	0.03	1	0.04	0.07	1	0.04	0.03	0.07	0.06

APPENDIX 5

The following plots show the significance rate of parameters in the models. The 0.05 level of significance was used. Dashed lines indicate 0.05 and 0.80 respectively.

Figure 6

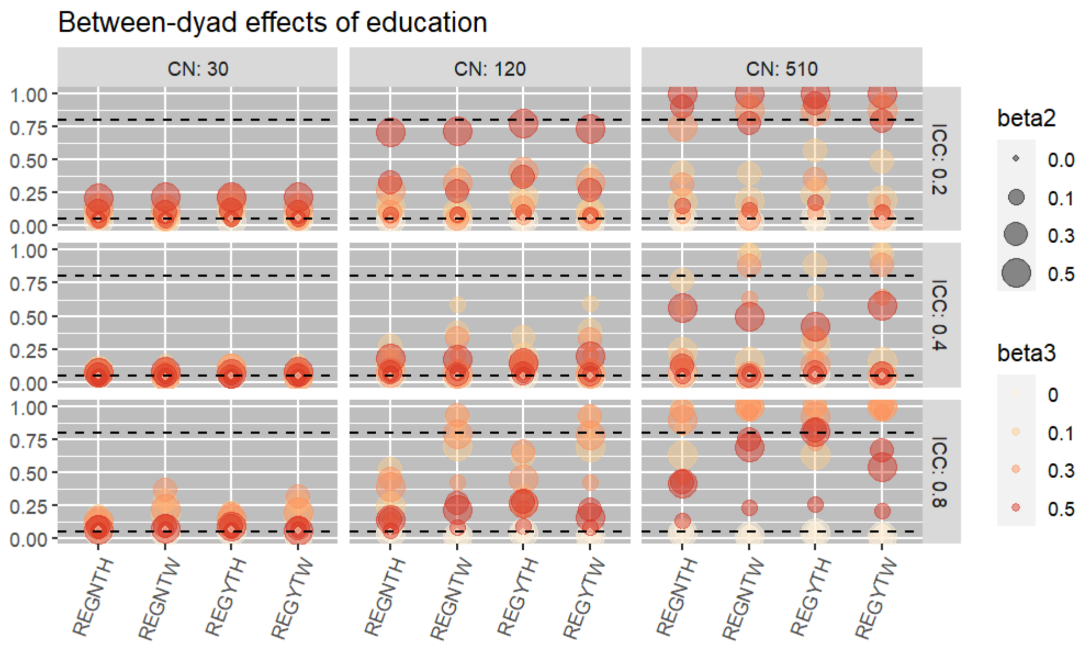
The Significance rate of within-dyad effect of education



Note. Beta2, and beta3 are from the data-generation equation. CN indicates the cluster numbers.

Figure 7

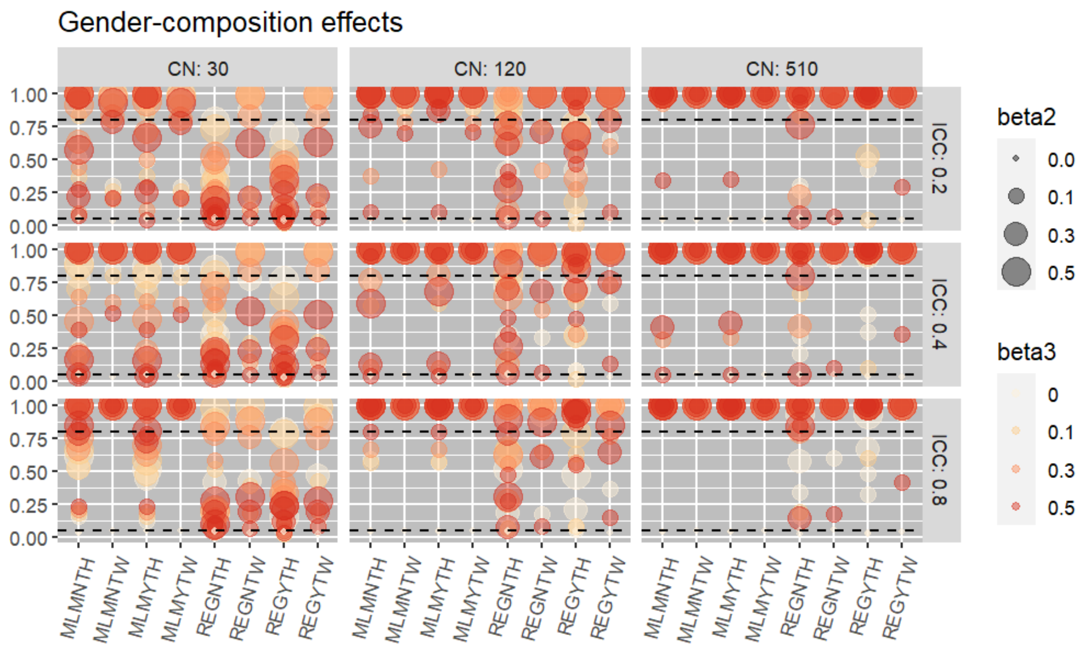
The significance rate of between-dyad effects of education



Note. Beta2, and beta3 are from the data-generation equation. CN indicates the cluster numbers.

Figure 8

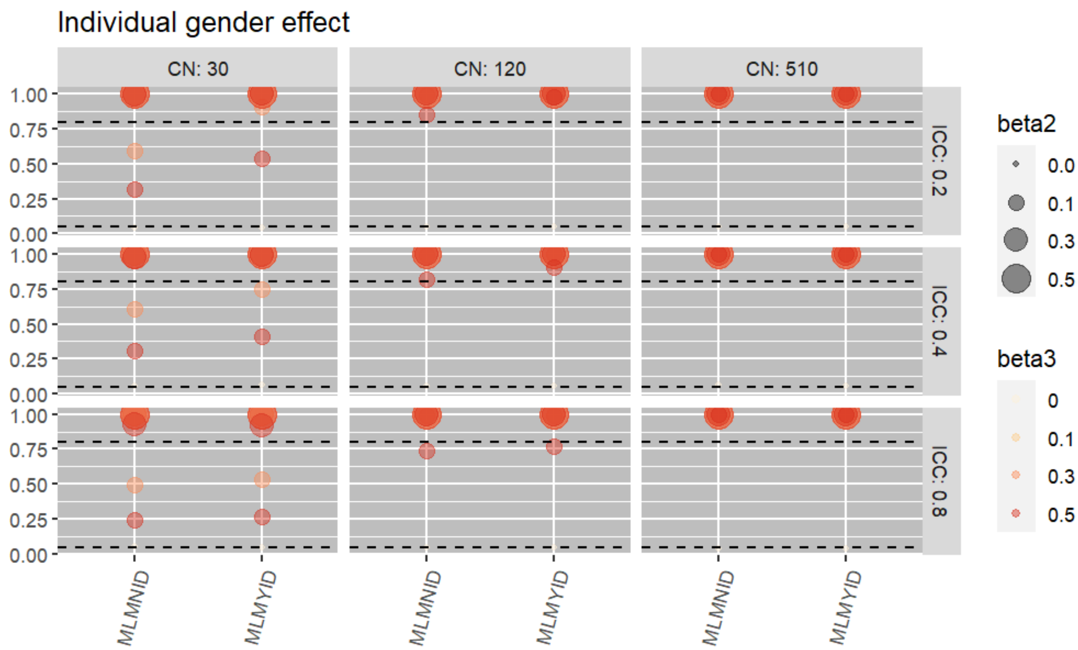
The significance rate of gender composition effects



Note. Beta2, and beta3 are from the data-generation equation. CN indicates the cluster numbers.

Figure 9

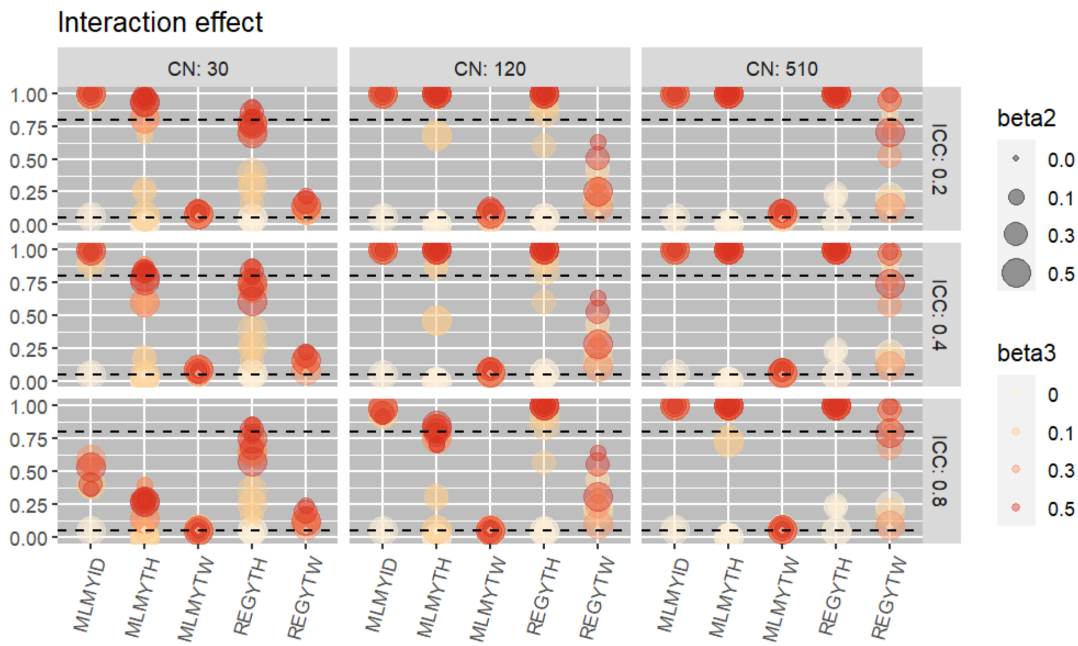
The significance rate of individual gender effect.



Note. Beta2, and beta3 are from the data-generation equation. CN indicates the cluster numbers.

Figure 10

The significance rate of interaction effect



Note. Beta2, and beta3 are from the data-generation equation. CN indicates the cluster numbers.

CURRICULUM VITAE

EDUCATION

Expected Aug 2022 **Wake Forest University, North Carolina**
M.A. in General Psychology
Thesis: *Dueling Dyads: Regression versus MLM Analysis with a Categorical Predictor*
(Advisor: S. Mason Garrison)

2018 **Sogang University, Seoul, Korea**
M.A. in Psychology
Thesis: *Cultural Differences in the emotional reactions to the negative events of an in-group member*
(Advisor: Jinkyung Na)

2014 **Hankuk University of Foreign Studies, Seoul, Korea**
B.A. in English Literature
Major: English Literature
Minor: Philosophy

SCHOLARSHIPS

2020 – 2022 Teaching/Research Assistantship
Wake Forest University
(Full tuition waiver and stipend. Approximately $104,000)

Apr 2021 Emerging Scholar and Diversity Award
Association for Research in Personality ($200)

Spring & Fall 2017 National Humanities and Social Science Graduate Research Scholarship,
Korea Student Aid Foundation ($8,000)

Fall 2012 National Scholarship (Income-based Grant),
Korean Government ($870)

PRESENTATION

1. **Hwang. Y.** (May 2021). *Breaking down the components of the SES-health gradient with sibling comparison.* Poster presented at 2021 First-year project presentation at Wake Forest University on Zoom
2. **Hwang. Y.** (Nov 2018). *Cultural Differences in the emotional reactions to the negative*

events of an in-group member. Talk presented at the Korean Social and Personality Psychological Association Symposium. Chuncheon, Korea.

CONFERENCE POSTERS

1. Good, R., **Hwang, Y**., & Garrison, S. M. (Jun 2022). *Patterns of Alcohol Use in a Military Subsample A sibling Comparison Design.* Poster presented at Behavior Genetics Annual Meeting in Los Angeles, CA.
2. Good, R., **Hwang, Y**., & Garrison, S. M. (Jun 2021). *Liquor Legacies: The impact of parental psychopathology and young adult depression on alcohol use*. Pre-Recorded Mini-Presentation presented at Behavior Genetics Annual Meeting on Zoom.
3. **Hwang, Y**., Trattner, J., & Garrison, S. M. (Jun 2021). *Breaking down the components of the SES-health gradient with sibling comparisons*. Pre-Recorded Mini-Presented at Behavior Genetics Annual Meeting on Zoom.
4. Mao, T. S., **Hwang, Y**., Trattner, J., Garrison, S. M. (Jun 2021). *Perspective of Gender Roles in the Family versus Personality Trait*s. Pre-Recorded Mini-Presentation at Behavior Genetics Annual Meeting on Zoom.
5. **Hwang, Y**. & Garrison, S. M. (May 2021). *Exploring the Components of Socio-Economic Status and Their relationship with health*. Poster presented at 2021 APS Annual Convention on Zoom
6. Mao, T. S., **Hwang, Y**., Trattner, J., Garrison, S. M. (Feb 2021). *Gender Roles Attitudes and Personality: A Sibling Comparison Design*. Poster presented at 2021 SPSP Annual Convention on Zoom
7. Huh, J., Na, J., Kang, M., Choi, Y., **Hwang, Y.** & Hong, S. (Feb 2019). *What Makes Koreans "Korean"? Ethnicity vs. Nationality*. Society for Personality and Social Psychology Annual Convention. Portland, OR.
8. **Hwang, Y**. & Na, J. (May 2018). *Cultural Differences: When an in-group member is being disrespected*. The Association for Psychological Science Annual Convention. San Francisco, CA.
9. Cho, M., **Hwang, Y**., Cho, Y., Hong, S. & Na, J. (Aug 2016). *The Effect of Calorie Information on the Perception of Hunger and Satiety*. Annual Conferences of Korean Psychology Association, Gunsan, South Korea.

WORKING MANUSCRIPTS

1. **Hwang, Y.** & Garrison, S. M. (In Prep). *Breaking down the components of the SES-health gradient with sibling comparison.*
2. **Hwang, Y**. & Na, J. (In Prep). *Cultural Differences in the emotional reactions to the negative events of an in-group member.*

RESEARCH EXPERIENCES & SKILLS

Wake Forest University, North Carolina
(Skills: R programming, mentoring undergrads, managing git hub repos, data analysis, simulation)
When a mixed variable is categorical in pooled-regression models and multilevel models (Master's research)
Breaking down the components of the SES-health gradient with sibling comparisons
Works in collaboration
Liquor Legacies: The impact of parental psychopathology and young adult depression on alcohol use
Gender Roles Attitudes and Personality: A Sibling Comparison Design

Sogang University, Seoul, Korea
(Skills: SPSS, mentoring undergrads, Qualtrics, Mturk, experiment, AMOS, SAS, Mplus)
Cultural differences in emotional experience (Master's research)
Cultural difference in emotion perception—which information is more important?
Works in collaboration
The Effect of Calorie Information on the Perception of Hunger and Satiety
What Makes Koreans "Korean"? Ethnicity vs. Nationality

RESEARCH POSITIONS

Wake Forest University
The R computing lab
Research Assistant
Grant: The National Institute on Aging (NIA) Fall 2021-Spring 2022
RF1-AG073189: "Quantifying the contributions of mitochondrial DNA to Alzheimer's Disease and related condition of Aging."
Research Assistant Summer 2021, Summer 2022

TEACHING POSITIONS

Wake Forest University
Teaching Assistant, Department of psychology Spring 2021
Methods in Psychological Research (Psy 310)
Industrial/Organization Psychology (Psy 268)
Teaching Assistant, Department of psychology Fall 2020
Introductory Psychology (Psy 151)
Cognitive Psychology (Psy 248)

Sogang University, Seoul, Korea
Teaching Assistant, Department of psychology Spring 2016
Multicultural Psychology
Introduction to Counseling Theories

Teaching Assistant, Department of Global Korean Studies Fall 2016
International Politics of Korean Peninsula
Globalization and Korean Development Theories
Teaching Assistant, School of General Education Spring 2017
Human beings & Intellectuality
Teaching Assistant, School of General Education Fall 2017
Man and Humanity

PROFESSIONAL EMPLOYMENT

Employee, TENSPACE Co. Ltd., Seoul, South Korea 2020
TENSPACE develops AI-based tools that use social media accounts to estimate the individuals' likelihood of repaying their loans
Responsibilities:
Reviewed literature on personality, social media, and loan repayment.
Discussed how research in academia can be applied to these tools.

ADVANCED TRAINING

fMRI Hands-on Training Workshop. Sungkyunkwan University, Seoul, Korea. Jan 2018

CERTIFICATION

Survey Analyst, Junior, Statistics Korea 2015

TECHNICAL SKILLS

R, SPSS, GitHub, AMOS, Mplus, SAS, Qualtrics, Mturk