The Effect of Cross-loading on Measurement Equivalence of Psychometric Multidimensional Questionnaires in MIMIC Model: a Simulation Study

Jamshid Jamali¹,², Seyyed Mohammad Taghi Ayatollahi³, Peyman Jafari³

ABSTRACT

Introduction: In recent years, Multiple Indicators Multiple Causes (MIMIC) model has been widely used to assess measurement invariance, called Differential Item Functioning (DIF) analyses, in psychological and medical studies. Aim: This simulation study aimed at assessing the effect of sample size, scale length, and magnitude of the uniform-DIF on detecting uniform-DIF with the MIMIC model when it has cross-loading in multidimensional scales. Material and Methods: In this Monte Carlo simulation study, we calculated power, Type I error rates, the bias of parameters estimation, Coverage Probability (CP), and Convergence Rate (CR) was used to assess the performance of the MIMIC model. The means of RMSEA, SRMR, CFI, and TLI, as indices of the goodness-of-fit for the MIMIC model, were computed across 1000 replications for each simulation condition. Result: Approximately, in all scenarios simulated, the bias of DIF parameters estimation was negligible. The existence of cross-loading caused a decrease of approximately 11.8% in the power and increase of 0.04-unit in bias parameter estimation. By increasing the relationship between dimensions, the power and CP of MIMIC model decreased, however, bias and CR were increased. In all scenarios that were performed in this study, all goodness-of-fit indices were at an acceptable level. Conclusion: Our results indicated that the performance of the MIMIC model improved, when sample size, the number of items, and the magnitude of DIF increased. When the scale is multidimensional and model have cross-loading, the performance of the MIMIC model becomes questionable.

Keywords: Reproducibility of Results, Monte Carlo Method, Psychometrics, Surveys and Questionnaires.

1. INTRODUCTION

Many scientific fields including medicine and psychometric studies deal with the design, construction or translation of questionnaires. The validity and reliability are the two most important concepts related to questionnaires. In recent years, measurement equivalence, also known as differential item functioning (DIF), has been widely used to evaluate the validity and reliability of questionnaires (1-5). DIF occurs when item’s response function changes across different groups of respondents. It means that participants’ perception of questionnaire’s item differs across groups, after controlling for the certain construct (6, 7).

Numerous statistical approaches are designed to detect DIF (6, 8, 9). Structure Equation Modeling-based methods (SEM) with appropriate statistical properties are popular procedures for detecting DIF. Multiple Indicators Multiple Causes (MIMIC) model, an SEM-based DIF detection method, involves using latent variables that are predicted by observed variables (10). This method does not require unidimensionality and conditional independence assumptions (11). The MIMIC model does not need large sample size, provides information about the structural and measurement model, does not have a special restriction on the variable scale, each latent variable can be predicted by at least one observed indicator, and can
detect DIF in the multidimensional questionnaire (1, 12-16).

To identify DIF in the traditional MIMIC model, for each dimension of the instrument has to be fitted with one MIMIC model (17). Using this approach, apart from increasing the error rate, the relationship between instrument dimensions ignored. Consequently, in the recent year, several methods have been proposed to detect DIF in multidimensional questionnaires (18, 19). Divergent validity, also known as discriminant validity, is a technique to assess the construct validity of a questionnaire. In the well-designed questionnaire, an item must have a high correlation with the other items in the same dimension but have low correlation with items in other dimensions (20, 21). SEM-based applied research is typically including cross-loadings but it can lead to misspecifying the model (10). Misspecification of the MIMIC model can lead to biased coefficients and error terms, which in turn can produce incorrect inference in DIF testing (22-24).

2. MATERIALS AND METHODS

2.1. MIMIC Model for Detecting DIF

In DIF study, uniform (constant across ability levels) and non-uniform (varying across ability levels) can be identified, but in our simulation study, we only looked at uniform-DIF. The uniform-DIF is important amongst applied researchers because the non-uniform-DIF has an interaction between ability level and group membership (17, 25). Uniform-DIF occurs when item thresholds differ between groups. In the MIMIC model, an item is tested for uniform-DIF by regressing it and latent variable (ability) onto a covariate simultaneously (26).

2.2. Simulation

Data and matrix generation are two methods for simulations in SEM. In DIF simulation studies using data generation, responses were generated from a common model, for example, Graded Response Model. Usually, if scale variables and relationships between the indicator variables with each other or with latent variables are important, the researcher uses the data generation. In order to generate raw data this method has higher accuracy and is more realistic. Due to the computational complexity of some matrix iterative algorithms in estimating MIMIC parameters, as well as the complex relationship between variable, hence we cannot always generate raw data. In matrix generation approach, the relationships between variables are redesigned with correlation and covariance matrix. Using this method leads to saving time, and provides the possibility of testing the hypotheses that cannot be evaluated by raw data. In this simulation study, five factors of sample size, the number of items in each dimension, the magnitude of uniform-DIF, the correlation between dimensions, and cross-loading were investigated. The sample size was set at 100, 250, and 500 for the small, moderate, and large sample

Figure 1. A MIMIC model used to detect uniform-DIF in this study
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### 3. RESULTS

#### 3.1. Sample size effect on detecting uniform-DIF in the MIMIC model

When other conditions stayed fixed, increasing the sample size led to improving the power of the MIMIC model. The mean±SD power of MIMIC model in the sample size of 100, 250 and 500 were 0.61±0.32, 0.72±0.27, and 0.77±0.21, respectively. The mean±SD of parameter estimation’ bias in the sample size of 100, 250 and 500 were 0.07±0.05, 0.06±0.03, and 0.06±0.04, respectively, where a meaningful change was not observed. The mean±SD CP of DIF parameter in the sample size of 100, 250 and 500 were 0.89±0.05, 0.82±0.10, and 0.75±0.16, respectively, these numbers indicate that increase in sample size leads to reduce CP. The CR of iteration in the sample size of 100, 250 and 500 were 90.24±6.47, 86.94±8.81, and 83.80±10.27, respectively, which is an indication of reduced CR by increasing the sample size.

#### 3.2. Number of item effect on detecting uniform-DIF in the MIMIC model

By considering that other factors were constant, increasing the number of items from 5 to 10, led to the improvement of 0.67±0.28 to 0.73±0.27 in the power of the MIMIC model. The mean±SD of bias, CP, and CR were 0.06±0.04, 0.85±0.12, and 0.85±0.16, respectively, which is an indication of reduced CR by increasing the sample size.

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**Table 1. Evaluation the impact of cross-loading on uniform DIF detection in MIMIC model in sample size 100.** ρ: Correlation coefficient between the two dimensions; r: Cross-loading; MIMIC: Multiple Indicators Multiple Causes; DIF: Differential Item Functioning; CP: Coverage Probability; CR: Convergence Rate; RMSEA: Root Mean Squared Error of Approximate; SRMR: Standardized Root Mean Squared Residual; CFI: Comparative Fit Index; TLI: Tucker-Lewis Index

| Condition | magnitude of DIF | power | Bias | CP | CR | RMSEA | CFI | TLI | SRMR | power | Bias | CP | CR | RMSEA | CFI | TLI | SRMR |
|-----------|----------------|-------|------|----|----|-------|-----|-----|------|-------|------|----|----|-------|-----|-----|------|
| ρ=0 r=0 | small | 0.326 | -0.025 | 0.969 | 76.9 | 0.045 | 0.969 | 0.959 | 0.044 | 0.430 | 0.01 | 0.972 | 88.6 | 0.032 | 0.972 | 0.969 | 0.048 |
| medium | 0.748 | -0.017 | 0.978 | 78.5 | 0.043 | 0.972 | 1.002 | 0.043 | 0.857 | 0.025 | 0.962 | 86.8 | 0.031 | 0.973 | 0.997 | 0.049 |
| large | 0.898 | 0.015 | 0.968 | 78.3 | 0.044 | 0.971 | 0.962 | 0.043 | 0.960 | 0.015 | 0.950 | 87.5 | 0.031 | 0.975 | 0.972 | 0.049 |
| ρ=0 r=0.61 | small | 0.145 | 0.021 | 0.931 | 84.1 | 0.044 | 0.973 | 0.963 | 0.043 | 0.194 | -0.084 | 0.894 | 91.6 | 0.032 | 0.974 | 0.971 | 0.049 |
| medium | 0.573 | 0.011 | 0.935 | 83.2 | 0.041 | 0.975 | 0.966 | 0.042 | 0.709 | -0.038 | 0.875 | 89.6 | 0.032 | 0.974 | 0.971 | 0.048 |
| large | 0.864 | -0.011 | 0.928 | 79.2 | 0.044 | 0.974 | 0.966 | 0.042 | 0.939 | -0.098 | 0.878 | 90.1 | 0.032 | 0.975 | 0.972 | 0.049 |
| ρ=0.25 r=0.61 | small | 0.14 | 0.004 | 0.924 | 88.6 | 0.043 | 0.974 | 0.965 | 0.041 | 0.186 | -0.087 | 0.865 | 94.4 | 0.031 | 0.975 | 0.972 | 0.047 |
| medium | 0.582 | -0.150 | 0.903 | 86.6 | 0.042 | 0.976 | 0.967 | 0.042 | 0.727 | -0.086 | 0.854 | 95.2 | 0.032 | 0.975 | 0.972 | 0.047 |
| large | 0.897 | -0.093 | 0.902 | 87.6 | 0.044 | 0.974 | 0.965 | 0.042 | 0.954 | -0.059 | 0.858 | 95.3 | 0.032 | 0.975 | 0.972 | 0.048 |
| ρ=0.5 r=0.61 | small | 0.141 | -0.077 | 0.885 | 92.5 | 0.042 | 0.978 | 0.97 | 0.04 | 0.170 | -0.111 | 0.850 | 98.2 | 0.031 | 0.976 | 0.973 | 0.045 |
| medium | 0.604 | -0.010 | 0.882 | 91.5 | 0.042 | 0.976 | 0.968 | 0.041 | 0.745 | -0.086 | 0.829 | 98.2 | 0.031 | 0.977 | 0.974 | 0.045 |
| large | 0.93 | -0.098 | 0.875 | 91.9 | 0.043 | 0.978 | 0.971 | 0.041 | 0.969 | -0.094 | 0.840 | 98.2 | 0.031 | 0.976 | 0.973 | 0.046 |
| ρ=0.75 r=0.61 | small | 0.126 | -0.114 | 0.873 | 93.0 | 0.042 | 0.979 | 0.972 | 0.039 | 0.179 | -0.112 | 0.826 | 98.2 | 0.03 | 0.979 | 0.976 | 0.042 |
| medium | 0.646 | -0.108 | 0.859 | 92.2 | 0.043 | 0.979 | 0.972 | 0.039 | 0.748 | -0.116 | 0.813 | 98.9 | 0.031 | 0.979 | 0.976 | 0.043 |
| large | 0.94 | -0.146 | 0.859 | 93.4 | 0.041 | 0.981 | 0.974 | 0.039 | 0.983 | -0.092 | 0.824 | 98.8 | 0.030 | 0.979 | 0.976 | 0.043 |

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### Table 2. Evaluation the impact of cross-loading on uniform DIF detection in MIMIC model in sample size 250.

| Condition | magnitude of DIF | power | Bias | CP | CR | RMSEA | CFI | TLI | SRMR |
|-----------|-----------------|-------|------|----|----|--------|-----|-----|------|
| small     | 0.25            | 0.588 | 0.072 | 0.973 | 67.8 | 0.020 | 0.994 | 0.992 | 0.018 | 0.682 | 0.014 | 0.935 | 73.8 | 0.013 | 0.996 | 0.995 | 0.020 |
| medium    | 0.61            | 0.823 | 0.053 | 0.975 | 67.2 | 0.018 | 0.995 | 0.993 | 0.019 | 0.928 | 0.025 | 0.951 | 72.0 | 0.013 | 0.996 | 0.995 | 0.020 |
| large     | 0.75            | 0.864 | 0.076 | 0.722 | 95.1 | 0.026 | 0.992 | 0.999 | 0.024 | 0.927 | -0.095 | 0.704 | 99.0 | 0.017 | 0.993 | 0.992 | 0.027 |

### Table 3. Evaluation the impact of cross-loading on uniform DIF detection in MIMIC model in sample size 500.

| Condition | magnitude of DIF | power | Bias | CP | CR | RMSEA | CFI | TLI | SRMR |
|-----------|-----------------|-------|------|----|----|--------|-----|-----|------|
| small     | 0.25            | 0.446 | 0.026 | 0.685 | 87.4 | 0.018 | 0.996 | 0.994 | 0.018 | 0.494 | -0.158 | 0.515 | 93.6 | 0.012 | 0.996 | 0.996 | 0.019 |
| medium    | 0.61            | 0.878 | 0.020 | 0.672 | 88.2 | 0.018 | 0.996 | 0.994 | 0.018 | 0.919 | -0.060 | 0.585 | 94.5 | 0.012 | 0.996 | 0.996 | 0.020 |
| large     | 0.75            | 0.955 | -0.078 | 0.737 | 87.0 | 0.019 | 0.996 | 0.994 | 0.018 | 0.951 | -0.044 | 0.637 | 95.7 | 0.012 | 0.996 | 0.996 | 0.020 |

3.3. Magnitude of DIF effect on detecting uniform-DIF in the MIMIC model

When other factors are held constant during evaluation, with increasing severity of DIF, the power and CP of the MIMIC model were increased. However, no significant changes in bias and CR were observed. The means SD power in small,
A simulation study was conducted by Liaw that revealed a Type I error. This result concurs with the results of our study that increased the dimensions could lead to reduced power and increased the bias parameters. Lee et al., in their study found that increased relationship between the dimensions of the questionnaires that had led to reduced power and CP and increased the DIF. In previous studies, similar results were obtained. The performance of the MIMIC model in discovering uniform-DIF increased when sample size, the number of items and severity of DIF increased. When other conditions remained constant, the impact of cross-loading caused a decrease of approximately 11.8% in power and increase 0.04 unit in bias parameter estimation. When the MIMIC model did not have a cross-loading factor, the mean±SD of power, bias, CP, and CR were 0.69±0.20, 0.08±0.04, 0.81±0.08, and 87.68±5.39, respectively. When the relationship between dimensions (ρ=0.50) was moderate, the mean±SD of power, bias, CP, and CR were 0.68±0.25, 0.08±0.04, 0.81±0.09, and 87.70±5.90, respectively. When the relationship between dimensions (ρ=0.75) was strong, the mean±SD of power, bias, CP, and CR were 0.68±0.24, 0.08±0.04, 0.81±0.09, and 87.70±5.91, respectively. The results of the simulation showed that when the relationship between dimensions increased, the power and CP were decreased and bias and CR were increased.

### 3.4. Relationship between dimensions’ effect on detecting uniform-DIF in the MIMIC model

When there was no relationship between dimensions (ρ=0), the mean±SD of power, bias, CP, and CR were 0.71±0.24, 0.08±0.02, 0.92±0.07, and 78.79±6.71, respectively. When the relationship between dimensions (ρ=0.25) was weak, the mean±SD of power, bias, CP, and CR were 0.68±0.29, 0.08±0.04, 0.81±0.08, and 87.66±5.39, respectively. When the relationship between dimensions (ρ=0.50) was moderate, the mean±SD of power, bias, CP, and CR were 0.69±0.30, 0.08±0.04, 0.75±0.11, and 93.35±3.72, respectively. When the relationship between dimensions (ρ=0.75) was strong, the mean±SD of power, bias, CP, and CR were 0.68±0.29, 0.07±0.04, 0.78±0.11, and 89.62±7.41, respectively.

In all scenarios that were performed in this study, all goodness-of-fit indices were at an acceptable level. For more information about goodness-of-fit indices and performance assessment indicators of MIMIC model in uniform-DIF detection, refer to Tables 1 to 3.

### 3.5. Presence of cross-loading effect on detecting uniform-DIF in the MIMIC model

When other conditions remained constant, the existence of cross-loading caused a decrease of approximately 11.8% in the power and increase 0.04 unit in bias parameter estimation. When the MIMIC model did not have a cross-loading factor, the mean±SD of power, bias, CP, and CR were 0.76±0.19, 0.03±0.02, 0.96±0.01, and 76.47±6.64, respectively. When the MIMIC model had a cross-loading factor, the mean±SD of power, bias, CP, and CR were 0.68±0.29, 0.07±0.04, 0.78±0.11, and 89.62±7.41, respectively.

### 4. DISCUSSION

Due to MIMIC model flexibility in DIF detection, this model has become an increasingly popular method to detect DIF. In this simulation-based study, we evaluated the impact of cross-loading and relationship between the dimensions on the performance of the MIMIC model in discovering uniform-DIF.

The results of our study showed that increasing the sample size, the number of items and severity of DIF could improve the performance of the MIMIC model for detecting uniform-DIF. In previous studies, similar results were obtained. The results of this study showed the relationship between the dimensions of the questionnaires that had led to reduce power and CP and increase the bias parameters. Lee et al., in their study found that increase relationship between the dimensions could lead to reduced power and increased the Type I error. This result concurs with the results of our study (19). A simulation study was conducted by Liaw revealed that by increasing the relations between dimensions, multidimensional item response theory (MIRT) approach have a low bias in estimating the parameters and the relatively appropriate statistical power level in DIF detection (33). Finch et al., in their study, showed that by increasing the severity of the relationship between the dimensions of the questionnaire, bias, standard error, and root mean square error (RMSE) of item parameter estimates in two and three-parameter logistic MIRT was increased (34). In another study, Batley and Bose showed that standard deviation and standard error in the MIRT were not affected by the increased severity of the relationship between the dimensions of the questionnaire (35).

Another important feature considered in this study was the evaluation of cross-loading that could affect the performance of the MIMIC model. Cross-loading items are a major source of insufficient discriminant (36). Aside from the methodological problems, the results interpretation of MIMIC model with cross-loading is difficult. Previous studies have shown that the assessment of cross-loadings has not an appropriate measure for evaluating the discriminant validity in the questionnaire and this approach does not reliably identify the lack of discriminant validity in common research conditions (21). This method only works well in states with heterogeneous loading patterns and high sample sizes (21). However, the presence cross-loading in the model can lead to the misspecification the SEM (37). Our study showed that when the MIMIC model has a cross-loading factor, its performance is not appropriated. In other words, power and CP reduced and magnitude of the bias MIMIC model increased. However, the MIMIC model had acceptable power in uniform-DIF detection when the sample size was large or the magnitude of DIF was severe. To the best of our knowledge, the impact of cross-loading in DIF detection by the MIMIC model has not been investigated. Bauer in part of his study provided theoretical explanations about the impact of cross-loading on measurement equivalence in questionnaires (38). In this study, RMSEA, SRMR, CFI, and TLI indices were used to assess goodness-of-fit. As suggested by Taylor, RMSEA index is an appropriate index to assess goodness-of-fit in misspecification model (37). The results of our study indicated that all goodness-of-fit indices at acceptable levels; therefore, the results obtained in this study is reliable. Our study results should be viewed in light of its limitations. First, in this study, uniform-DIF was considered, although the MIMIC model could handle two type uniform and non-uniform-DIF. Second, we assume that the scale has two dimensions, one cross-loading, and one DIF items, while the MIMIC model can handle more conditions (19). Third, another limitation of this research was the relatively low number of reliable studies in this field to compare the result with it.
type of DIF, cross-loading, the relationship between dimensions of the performance of the MIMIC model for uniform DIF detection when scale have more than two dimensions.

- **Abbreviation:** MIMIC: Multiple Indicators Multiple Causes DIF: Differential Item Functioning, CP: Coverage Probability, CR: Convergence Rate, RMSEA: Root Mean Squared Error of Approximate, SRMR: Standardized Root Mean Squared Residual, CFI: Comparative Fit Index, TLI: Tucker-Lewis Index, MIRT: Multidimensional Item Response Theory.

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