

# Can Fit Indices Yielded from the SAS® GLIMMIX Procedure Select the Accurate Q-matrix?

Yan Wang, Yi-Hsin Chen, Isaac Y. Li, Chunhua Cao  
University of South Florida

## ABSTRACT

In educational diagnostic assessments, it is not uncommon to develop several competing Q-matrices that specify item-and-attribute relations and select the best fit Q-matrix among them to make valid inferences about students' strengths and weaknesses of cognitive attributes. Thus, selecting an accurate Q-matrix plays a crucial role in making valid inferences in diagnostic analyses. This study is intended to examine the effectiveness of fit indices yielded from the SAS GLIMMIX procedure for selecting the accurate Q-matrix using the cross random effects linear logistic test model (CRE-LLTM). A simulation study is designed and six fit indices (i.e., log likelihood, AIC, AICc, BIC, CAIC, and HQIC) are examined. Five design factors are manipulated, including sample size (50, 250, and 500), population distribution (normal, slightly positively skewed, slightly negatively skewed, positively skewed, and negatively skewed), percentage (2.4%, 4.8%, and 9.6%) and type (over, under, and balanced) of the Q-matrix misspecification as well as the Q-matrix density (sparse and dense). The number of items is fixed to be 21 with 8 attributes. Data sets are simulated using the SAS/IML package. For each condition, 1000 replications are generated. The selection accuracy of fit indices is defined as the proportion of replications where the true Q-matrix is selected based on smaller values of fit indices. In addition, factorial ANOVA analyses with the generalized eta-squared effect size are employed to examine the impact of the manipulated factors on selecting the true Q-matrix. The results indicate that the overall performance of the six fit indices is similar. Not surprisingly, when the misspecification percentage is larger (e.g., 9.6%), fit indices can be more accurate to select the true Q-matrix regardless of the Q-matrix density, misspecification type, and sample size. The presence of negatively skewed distribution of cognitive attributes with a small percentage of misspecification or the balanced type of misspecification would lead to less accurate selection of the true Q-matrix.

## INTRODUCTION

### CROSS RANDOM EFFECT LINEAR LOGISTIC TEST MODEL (CRE-LLTM)

The linear logistic test model (LLTM) that incorporates cognitive task characteristics into the Rasch model has been widely used for various purposes in educational contexts, such as item selection, test development, construct validation, and so on. The LLTM is built upon the Rasch model so it is often considered an extension of the Rasch model (Chen, MacDonald, & Leu, 2011). To express the mathematical equation for the LLTM, the Rasch model is presented first as follows:

$$P(X_{ij} = 1 | \theta_j, \beta_i) = \exp(\theta_j - \beta_i) / [1 + \exp(\theta_j - \beta_i)],$$

where  $P(X_{ij}=1)$  represents the probability of the correct response to item  $i$  for person  $j$ ,  $\theta_j$  is the ability level of person  $j$ , and  $\beta_i$  is the item difficulty of item  $i$ . When a linear combination of cognitive attributes replaces item difficulty,  $\beta_i$ , the Rasch model can be written into the LLTM formula as follows:

$$P(X_{ij} = 1 | \theta_j, q_{ik}, \eta_k) = \exp(\theta_j - \sum_{k=1}^K q_{ik} \eta_k + c) / [1 + \exp(\theta_j - \sum_{k=1}^K q_{ik} \eta_k + c)].$$

That is, in the LLTM the item difficulty parameter is replaced by cognitive attributes which can be conceptualized as

$$\hat{\beta}_i = \sum_{k=1}^K q_{ik} \eta_k + c,$$

where  $q_{ik}$ , an entry in a so-called Q-matrix, is the fixed and known weight (occurrence) assigned to cognitive attribute  $k$  that is involved in item  $i$  and  $\eta_k$  is the estimated parameter for cognitive attribute  $k$ , and  $c$  is the normalizing constant and is simply defined as the mean of the  $\beta_i$  estimates under the Rasch model.

However, the LLTM model assumes that the variance of item difficulties is completely accounted for by cognitive attributes (i.e.,  $\beta_i = \hat{\beta}_i$ ). This can be considered a disadvantage of the LLTM for the purpose of decomposing item

difficulty into cognitive attributes (Hartig, Frey, Nold, & Klieme, 2012). Janssen and De Boeck (2002) also observed that even though the Q-matrix is well designed and cognitive attributes well explain the majority of the variation in item difficulties, the LLTM often does not fit the data (Rijmen & de Boeck, 2002). To overcome the disadvantages of the LLTM, Janssen and colleagues (2004) proposed the crossed random-effects LLTM by adding the error term on item difficulty (i.e.,  $\beta_i = \hat{\beta}_i + \varepsilon_i$ ).

## THE SAS GLIMMIX PROCEDURE

The GLIMMIX procedure is a newly-developed package in SAS. Historically, this procedure could be applied from a SAS macro as an add-on product in SAS 9.1. Now as an individual package, a lot of improvements have been made in SAS 9.3 (Li, Chen, & Kromrey, 2013). The SAS PROC GLIMMIX performs estimation and statistical inference for generalized linear mixed models (GLMMs) that extends the class of generalized linear models (GLMs) by incorporating normally distributed random effects. The GLIMMIX procedure has been applied to formulate few IRT-related models compared to PROC NLMIXED and there has been only one study that examined its efficiency in parameter recovery (e.g., Cao, Wang, Chen, & Li, 2014).

## Q-MATRIX

A Q-matrix specifies the item-attribute relationship in cognitive diagnostic models (e.g., Madison & Bradshaw, 2014). It is an item-by-attribute matrix consisting of 1s and 0s which indicates a positive endorsement on an item and requires a particular cognitive attribute or not respectively. As a prerequisite to accurate estimation of examinees' skill competencies, the construction and validation of Q-matrices have been widely applied in educational and psychological assessments. For instance, using the Q-matrix to identify the relationship between test items and cognitive attributes (or constructs of interest) has been recognized as the critical step in the diagnostic analyses of students' reading and/or listening comprehension skills (e.g., Jang, 2009; Sawaki, Kim, & Gentile, 2009).

In educational assessments, establishing the Q-matrix is an iterative process that requires multiple sources of evidence to support the link between test items and the cognitive attributes measured. Typically, it involves content experts, examinees, and psychometricians in a concerted effort to provide theoretical and empirical evidence for the Q-matrices. It is very often to have several competing Q-matrices in the process of selecting the most appropriate Q-matrix for cognitive skill analyses.

Since the accuracy of Q-matrix is very important to make valid inferences in terms of cognitive skills based on psychometric models of interest (e.g., LLTM, CRELLTM, DCMs) (Kunina-Habenicht, Rupp, & Wilhelm, 2012), the impact of Q-matrix misspecification has been examined in some methodological studies. For example, Rupp and Templin (2008) investigated the Q-matrix overfit (0s misspecified as 1s), underfit (1s misspecified as 0s), balanced misfit (0s misspecified as 1s and 1s misspecified as 0s), and misfit that occurs only to particular attributes. They focused on the influence of those types of Q-matrix misspecification on parameter estimates and misclassification rates. Kunina-Habenicht, Rupp, and Wilhelm (2012) also examined the influence of different types of Q-matrix misspecification on AIC and BIC (see the section below). Since it is common to use fit indices to evaluate the accuracy of Q-matrices, this study will further explore the sensitivity of several widely used fit indices to Q-matrix misspecification under manipulated simulation conditions within the framework of CRE-LLTM. The following section introduces fit indices that are examined in this study.

## FIT INDICES

To select the best fitting Q-matrix, it is common that researchers use various fit indices yielded from the software packages and compare the values of these fit indices for competing Q-matrices. Based on the output of the SAS GLIMMIX procedure to estimate CRELLTM, five fit indices were considered in this study: -2 Log-Likelihood (-2LL), Akaike's Information criterion (AIC), Small Sample Size Corrected AIC (AICc), the Bayesian Information Criterion (BIC), consistent Akaike's information criterion (CAIC), and Hannan-Quinn Information Criterion (HQIC). Table 1 presents the formulae of these fit indices in detail.

CRE-LLTM with SAS GLIMMIX has been applied to select the best fitting Q-matrix in real data scenarios (e.g., Ferster, 2013); however, the effectiveness of the fit indices associated with SAS GLIMMIX has not been studied. In a study investigating the relative and absolute fit evaluation in cognitive diagnostic analysis (CDM) (Chen, de la Torre, & Zhang, 2013), BIC and AIC demonstrated sensitivity to detect misspecification of the CDM or Q-matrix misspecifications. Kunina-Habenicht, Rubb, and Wilhem (2012) conducted a series of simulation studies to investigate the impact of model misspecification on parameter estimation and item-fit in CDM, and the results suggested that both AIC and BIC were sensitive to Q-matrix misspecification. However, the other fit indices, like -2LL, AICc, CAIC, and HQIC have not been studied in CDM.

| Fit Index | Formula                                                                                             | Definition                                                                                                                                                                                                       |
|-----------|-----------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| -2LL      | $ML = \prod_{i=1}^N \sum_{l=1}^L L(X_i   \hat{\beta}, \alpha_l) p(\alpha_l)$<br>$-2LL = -2\log(ML)$ | $N$ = the sample size;<br>$L$ = the total number of attribute patterns;<br>$X_i$ = the response vector for examinee $i$ ;<br>$\alpha_l$ = the $l$ th attribute vector;                                           |
| AIC       | $AIC = -2LL + 2q$                                                                                   | $L(X_i   \hat{\beta}, \alpha_l)$ = the likelihood of the response vector of examinee $i$ given $\alpha_l$ ;<br>$p(\alpha_l)$ = the prior probability of $\alpha_l$ .<br>$q$ = the number of estimated parameters |
| AICc      | $AICc = -2LL + 2qN / (N - q - 1)$                                                                   |                                                                                                                                                                                                                  |
| BIC       | $BIC = -2LL + q\log(N)$                                                                             |                                                                                                                                                                                                                  |
| CAIC      | $CAIC = -2LL + 2q(\log N + 1)$                                                                      |                                                                                                                                                                                                                  |
| HQIC      | $HQIC = -2LL + 2q\log\log(N)$                                                                       |                                                                                                                                                                                                                  |

**Table 1. Formulae of Fit Indices**

## RESEARCH PURPOSE AND QUESTIONS

This simulation study, therefore, aims at investigating the sensitivity of the fit indices yielded from the SAS GLIMMIX procedure under different types and percentages of Q-matrix misspecification, as well as the impact of the design factors on these fit indices. Research questions were as follows:

1. Which fit index (i.e., -2LL, AIC, AICc, BIC, CAIC, and HQIC) examined in this study can select the true Q-matrix more accurately?
2. Which design factors have the significant impact on selecting the true Q-matrix among these fit indices?

## METHOD

### DESIGN FACTORS

This simulation study had five design factors. The sample sizes were 50, 250, and 500. The population distribution included normal (skewness=0, kurtosis=0), slightly positively skewed (skewness=1, kurtosis=3), slightly negatively skewed (skewness=-1, kurtosis=3), positively skewed (skewness=2, kurtosis=6), and negatively skewed (skewness=-2, kurtosis=6) distributions. The percentages of misspecification in the Q-matrix were 2.4% (4 entries), 4.8% (8 entries), and 9.6% (16 entries). Three types of misspecification were over-misspecification (0s→1s), under-misspecification (1s→0s), and balanced-misspecification (0s→1s and 1s→0s). The density of Q-matrix included sparse Q-matrices with 48 out of 168 entries containing 1s (approximately 30% 1s), and dense Q-matrices with 96 out of 168 entries containing 1s (approximately 60% 1s). Therefore this fully crossed factorial design yielded a total of 270 (3\*5\*3\*3\*2) conditions. For each condition, 1000 replications were generated. Data were simulated based on the CRE-LLTM model using the SAS/IML package.

Like Baker's (1993) study, the sparse and dense Q-matrices were extracted from Fischer and Formman (1972) and Medina-Diaz (1993), respectively. The true cognitive attribute parameters for the sparse Q-matrix were  $\eta_1 = 2.152$ ,  $\eta_2 = 1.229$ ,  $\eta_3 = -.468$ ,  $\eta_4 = 1.907$ ,  $\eta_5 = 1.051$ ,  $\eta_6 = .086$ ,  $\eta_7 = .141$ , and  $\eta_8 = -.474$ . A total of 21 items with 8 cognitive attributes was involved in the original sparse Q-matrix in Baker's (1992) study. As seen in Table 2, the sparse Q-matrix had only 48 out of 168 entries that contained 1s (approximately 30% 1s). And the dense Q-matrix had 96 out of 168 entries that contained 1s (approximately 60% 1s) as shown in Table 3. Misspecified entries in the Q-matrix were randomly assigned using SAS based on design factors of misspecification percentage and type mentioned in the previous paragraph.

| Item  | Cognitive Attribute |   |   |   |   |   |   |   | Total |
|-------|---------------------|---|---|---|---|---|---|---|-------|
|       | 1                   | 2 | 3 | 4 | 5 | 6 | 7 | 8 |       |
| 1     | 0                   | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 2     |
| 2     | 1                   | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 3     |
| 3     | 0                   | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 2     |
| 4     | 1                   | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 3     |
| 5     | 0                   | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 2     |
| 6     | 0                   | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 2     |
| 7     | 0                   | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 3     |
| 8     | 0                   | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 2     |
| 9     | 1                   | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 2     |
| 10    | 1                   | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 3     |
| 11    | 0                   | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 2     |
| 12    | 0                   | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1     |
| 13    | 0                   | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 2     |
| 14    | 0                   | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 3     |
| 15    | 0                   | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 2     |
| 16    | 0                   | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 2     |
| 17    | 0                   | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1     |
| 18    | 0                   | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 3     |
| 19    | 0                   | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 2     |
| 20    | 1                   | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 2     |
| 21    | 0                   | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 2     |
| Total | 5                   | 5 | 5 | 5 | 5 | 5 | 9 | 9 | 48    |

**Table 2. The Sparse Q-matrix**

| Item  | Cognitive Attribute |    |    |    |    |    |    |    | Total |
|-------|---------------------|----|----|----|----|----|----|----|-------|
|       | 1                   | 2  | 3  | 4  | 5  | 6  | 7  | 8  |       |
| 1     | 1                   | 0  | 1  | 0  | 1  | 1  | 0  | 0  | 4     |
| 2     | 0                   | 0  | 0  | 1  | 0  | 1  | 0  | 1  | 3     |
| 3     | 0                   | 1  | 1  | 1  | 0  | 0  | 1  | 0  | 4     |
| 4     | 1                   | 1  | 0  | 0  | 1  | 0  | 0  | 0  | 3     |
| 5     | 0                   | 0  | 1  | 0  | 0  | 1  | 1  | 1  | 4     |
| 6     | 0                   | 1  | 0  | 1  | 0  | 1  | 0  | 1  | 4     |
| 7     | 1                   | 0  | 1  | 0  | 1  | 0  | 1  | 0  | 4     |
| 8     | 1                   | 0  | 0  | 1  | 0  | 1  | 1  | 0  | 4     |
| 9     | 0                   | 1  | 1  | 0  | 1  | 1  | 0  | 1  | 5     |
| 10    | 1                   | 1  | 0  | 1  | 0  | 1  | 0  | 1  | 5     |
| 11    | 1                   | 1  | 0  | 1  | 0  | 1  | 0  | 0  | 4     |
| 12    | 0                   | 0  | 1  | 1  | 1  | 0  | 1  | 0  | 4     |
| 13    | 0                   | 1  | 1  | 0  | 1  | 0  | 1  | 1  | 5     |
| 14    | 1                   | 0  | 1  | 1  | 0  | 1  | 0  | 1  | 5     |
| 15    | 1                   | 1  | 0  | 1  | 1  | 0  | 1  | 0  | 5     |
| 16    | 0                   | 1  | 1  | 1  | 0  | 1  | 1  | 1  | 6     |
| 17    | 1                   | 1  | 0  | 1  | 1  | 0  | 1  | 1  | 6     |
| 18    | 1                   | 1  | 0  | 1  | 1  | 1  | 0  | 1  | 6     |
| 19    | 1                   | 0  | 1  | 1  | 1  | 1  | 1  | 0  | 6     |
| 20    | 1                   | 1  | 1  | 0  | 1  | 0  | 1  | 1  | 6     |
| 21    | 1                   | 1  | 1  | 0  | 1  | 1  | 1  | 1  | 7     |
| Total | 12                  | 12 | 12 | 12 | 12 | 12 | 12 | 12 | 96    |

**Table 3. The Dense Q-matrix**

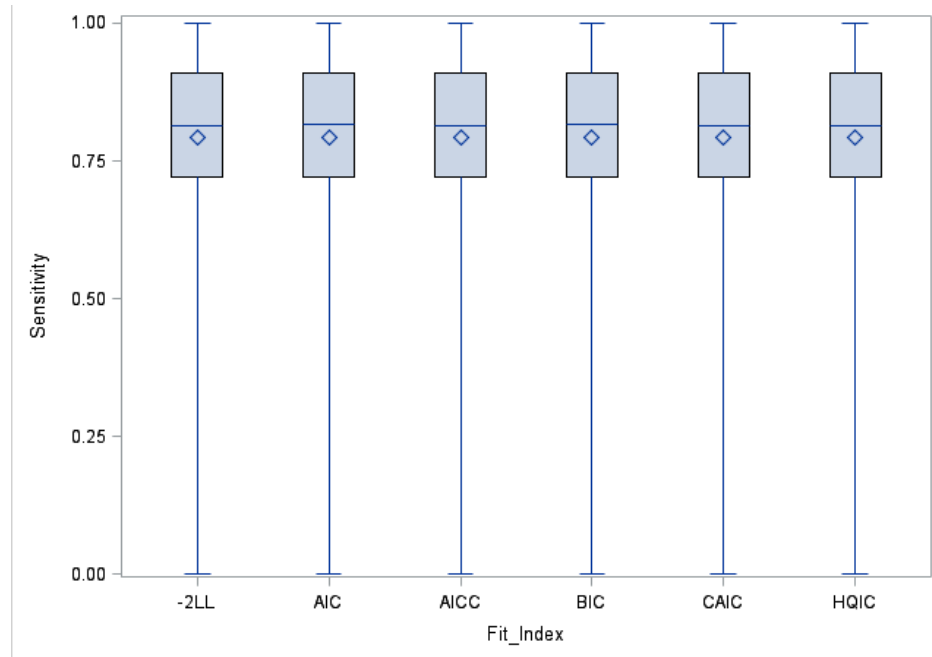
## ANALYTIC PROCEDURES

To answer the first research question on the performance of fit indices on selecting the true Q-matrix, the proportion of replications that selected the true Q-matrix, as indicated by smaller fit indices values out of 1000 replications was computed for each fit index in each simulated condition. In other words, if the fit index was sensitive to misspecification, we would expect high proportions of replications that selected the true Q-matrix. To address the second research question on the impact of design factors on the performance of fit indices, factorial ANOVA analyses with generalized eta-squared were used to examine what manipulated factors affect the fit indices. For each fit index, the proportion computed for the first research question was the dependent variable. Predictors were the design factors and the two-way interaction effects between those factors. Cohen's (1988) moderate effect size of .0588 was used as the significant level.

## RESULTS

### Performance of Fit Indices in Selecting the True Q-matrix

Figure 1 presents the overall performance of fit indices in the selection of true Q-matrix across all design factors. Sensitivity is defined as the proportions of replications that selected the true Q-matrix as indicated by small values of fit indices. As can be seen from Figure 1, a relatively large proportion of replications could select the true Q-matrix accurately for all the fit indices. Overall, they were sensitive to Q-matrix misspecification. In addition, the performance of six fit indices was very consistent in a way that they had similar proportions of replicatons that selected the true Q-matrix across the design factors.



**Figure 1. Overall Performance of Fit Indices in Selecting the True Q-Matrix**

Although Figure 1 showed that a high proportion of replications could select the true Q-matrix on average, there were some cases when all or none of the replications did the correct selection, as indicated by the extreme values of 1 and 0, respectively, on the boxplots. Simulation conditions that yielded those extreme values are presented in Tables 4 and 5. Results on Table 4 indicated that all fit indices did not perform well when the Q-matrix misspecification was balanced with a small percentage of entried (2.4%) misspecified. It seemed that when the distribution of cognitive attributes was negatively skewed, fit indices could not select the true Q-matrix.

| Misspecification Type | Q-Matrix Density | Distribution Shape | Percentage of Misspecification | Sample Size |
|-----------------------|------------------|--------------------|--------------------------------|-------------|
| Balanced              | Sparse           | Negatively Skewed  | 2.4                            | 50          |
| Balanced              | Sparse           | Negatively Skewed  | 2.4                            | 250         |
| Balanced              | Dense            | Positively Skewed  | 2.4                            | 500         |
| Balanced              | Dense            | Negatively Skewed  | 2.4                            | 50          |
| Balanced              | Dense            | Negatively Skewed  | 2.4                            | 250         |
| Balanced              | Dense            | Negatively Skewed  | 2.4                            | 500         |
| Over                  | Dense            | Normal             | 9.6                            | 500         |

**Table 4. Simulation Conditions with No Replication Selecting the True Q-Matrix**

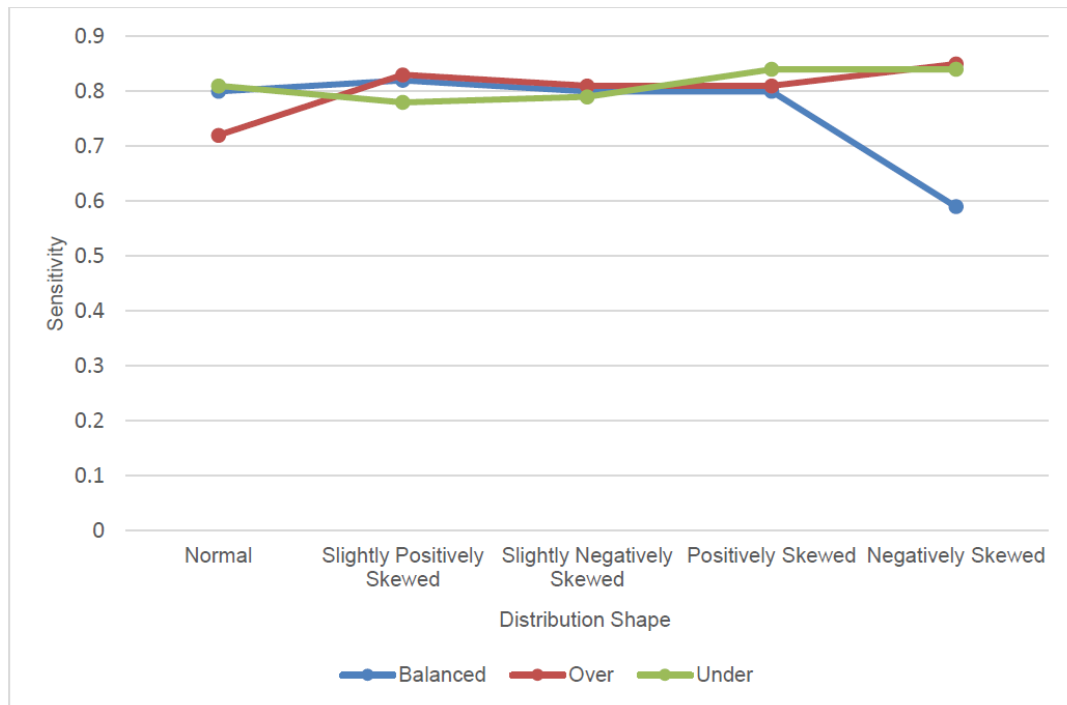
| Misspecification Type | Q-Matrix Density | Distribution Shape | Percentage of Misspecification | Sample Size |
|-----------------------|------------------|--------------------|--------------------------------|-------------|
| Balanced              | Dense            | Negatively Skewed  | 9.6                            | 500         |
| Over                  | Sparse           | Negatively Skewed  | 9.6                            | 50          |
| Over                  | Sparse           | Negatively Skewed  | 9.6                            | 250         |
| Over                  | Sparse           | Negatively Skewed  | 9.6                            | 500         |
| Over                  | Dense            | Positively Skewed  | 9.6                            | 500         |
| Over                  | Dense            | Negatively Skewed  | 9.6                            | 250         |
| Over                  | Dense            | Negatively Skewed  | 9.6                            | 500         |
| Under                 | Sparse           | Positively Skewed  | 4.8                            | 50          |

**Table 5. Simulation Conditions with All Replications Selecting the True Q-Matrix**

Interestingly, when the misspecification type was over and the distribution shape was negatively skewed, all fit indices performed extremely well that they could select the true Q-matrix 100%. A high percentage of misspecified entries in the Q-matrix (9.6%) seemed to yield high selection rates for the fit indices. Based on the results of the extreme cases with none or all replications selecting the true Q-matrix, it was indicated that the misspecification type, distribution shape, and percentage of misspecification might have an impact on the performance of those fit indices.

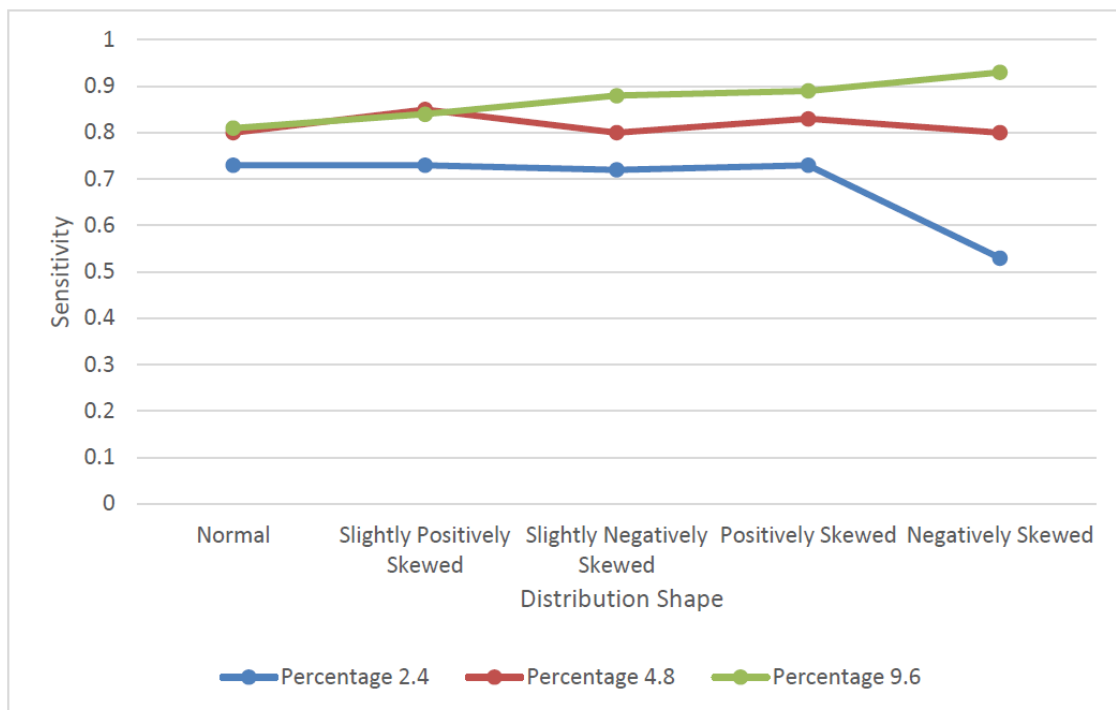
#### **Impact of Design Factors on the Performance of Fit Indices in Selecting the True Q-matrix**

Eta-squared analyses were conducted to examine the impact of design factors and their two-way interaction effects on the performance of fit indices in the selection of the true Q-matrix. Consistent with the results of the extreme cases shown above, the interaction between distribution shape and the type of misspecification had significant impact on the performance of fit indices. As presented in Figure 2, when the distribution shapes were slightly positively skewed, slightly negatively skewed, and positively skewed, selection rates of fit indices were very similar. When the cognitive attributes were normally distributed, fit indices had lower selection rates with entries in the Q-matrix misspecified as 1s. Selection rates of fit indices dropped dramatically with negatively skewed distribution of cognitive attributes and the balanced type of misspecification.



**Figure 2. Performance of Fit Indices by Distribution Shape and Type of Q-Matrix Misspecification**

The interaction between distribution shape and percentage of misspecification was another factor that had significant impact on the performance of fit indices. Figure 3 showed that a higher percentage of entries in the Q-matrix misspecified would lead to higher selection rates of fit indices. In other words, when the Q-matrix misspecification was more severe, it was more likely for fit indices to detect the misspecification. With negatively skewed data and 2.4% of entries misspecified, fit indices could not select the true Q-matrix accurately.



**Figure 3. Performance of Fit Indices by Distribution Shape and Percentage of Q-Matrix Misspecification**

## CONCLUSION

This simulation study examined the effectiveness of fit indices yielded from the SAS GLIMMIX procedure for selecting the accurate Q-matrix using the cross random effects linear logistic test model (CRE-LLTM) under various conditions. Across all design factor, the performance of the fit indices, including -2LL, AIC, AICc, BIC, CAIC, and HQIC, was very consistent. They all had relatively high selection rates, which indicated that they could detect the misspecification of Q-matrix very well, especially with a large proportion of 0s in the Q-matrix misspecified as 1s. With cognitive attributes negatively skewed, it was less likely for fit indices to detect the misspecification of Q-matrix, especially when some 0s were misspecified as 1s and some 1s misspecified as 0s in the Q-matrix. Overall when only a small proportion of entries in the Q-matrix was misspecified, fit indices were not very effective in detecting the misspecification. They could be even less effective if cognitive attributes were negatively skewed.

## REFERENCES

- Madison, M. J., & Bradshaw, L. P. (2014). The effects of Q-matrix design on classification accuracy in the log-linear cognitive diagnostic model. *Educational and Psychological Measurement*, 1-21.
- Baker, F. B. (1993). Sensitivity of the linear logistic test model to misspecification of the weight matrix. *Applied Psychological Measurement*, 17(3), 201-210.
- Jang, E. E. (2009). Demystifying a Q-matrix for making diagnostic inferences about L2 reading skills. *Language Assessment Quarterly*, 6(3), 210-238.
- Li, H. L., & Suen, H. K. (2013). Constructing and validating a Q-matrix for cognitive diagnostic analyses of a reading test. *Educational Assessment*, 18, 1-25.
- Rupp, A., & Templin, J. (2008). The effects of Q-matrix misspecification on parameter estimates and classification accuracy in the DINA model. *Educational and Psychological Measurement*, 68(1), 78-96.
- Kunina-Habenicht, O., Rupp, A. A., & Wilhelm, O. (2012). The impact of model misspecification on parameter estimation and item-fit assessment in log-linear diagnostic classification models. *Journal of Educational Measurement*, 49(1), 59-81.
- Sawaki, Y., Kim, H. J. & Gentile, C. (2009). Q-matrix construction: Defining the link between constructs and test items in large-scale reading and listening comprehension assessments. *Language Assessment Quarterly*, 6(3), 190-209.

## CONTACT INFORMATION

Your comments and questions are valued and encouraged. Contact the author at:

Yan Wang  
University of South Florida  
4202 E. Fowler Ave. EDU 368  
Tampa, FL 33647  
(813) 974-6064  
yanw@usf.edu

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