**Impact of Latent Traits Non-normality on Parameter Estimation in Bifactor Graded Response Model**

**Abstract**

Psychometric models, such as item response theory (IRT), usually assume a normal distribution of latent abilities or traits. Nonetheless, violations of normality assumption frequently occur in psychology and psychiatric research. Many researchers have investigated the impact of non-normality on IRT and other psychometric models, but insufficient attention has been given to its influence on bifactor IRT models, particularly with polytomous data. In this study, we address the problem of non-normality in parameter estimation within the framework of the bifactor-graded response model (Bifactor-GRM). The results indicate that non-normality in the general factor significantly impacts the accuracy of estimating general-factor discrimination and thresholds/locations but not limited impacts on specific-factor parameters. If specific factors have the non-normality issue, there are minor impacts on item parameter estimation for both the general and specific factors. Additionally, we found that increasing sample sizes and item numbers may reduce the impact of non-normality. Regarding person parameter estimation, the maximum a posteriori (MAP) algorithm generally outperforms marginal maximum likelihood (ML), particularly when population abilities or traits are non-normally distributed. To enhance the accuracy of the ML algorithm, researchers could increase sample sizes and item numbers.

*Keywords:* Bifactor model, graded response model, non-normality

**Introduction**

In psychological and educational measurement, the bifactor item response theory (IRT) model (Gibbons & Hedeker, 1992) has gained considerable attention in the past decades because of its ability to simultaneously model a general factor and specific factors underlying multidimensional constructs (DeMars, 2013; Heinrich at al., 2023; Reise at al., 2023; Rodriguez at al. 2016). In a bifactor model, item responses are a function of a general factor and a specific factor, and the specific factors are orthogonal to the general factor. Bifactor models have been widely applied in areas such as cognitive ability testing, personality assessment, and clinical psychology, where a separation between primary and secondary factors is preferred (add some citations here).

Many IRT models including bifactor models are estimated under the assumption that the latent traits conform to a (multivariate) normal distribution. This assumption is fundamental to the widely used marginal maximum likelihood estimation method (Bock & Aitkin, 1981; Bock & Lieberman, 1970), which treats latent trait as a random variable rather than a fixed parameter. The (multivariate) normal distribution is mathematically convenient and often serves as a reasonable approximation for many latent traits, particularly in the context of educational assessment. However, in many psychological and psychiatric contexts, this assumption may not be valid. For instance, in clinical assessments of psychiatric disorders, the majority of individuals tend to cluster at the lower end of the severity spectrum, while only a small subset exhibits extreme symptoms, leading to a positively skewed latent trait distribution. Similar patterns emerge in assessments of rare cognitive deficits or personality traits, where most individuals score within a typical range, and only a few deviate substantially. When the assumption of normality is violated, the accuracy of parameter estimation in IRT models may be compromised.

The impact of the non-normality of latent traits on parameter estimation has attracted attentions (e.g., Wang et al., 2018) in the field of structural equation modeling (Finch et al., 1997; Lai, 2018; Lei & Lomax, 2005; Maydeu-Olivares, 2017; Olsson et al., 2000; Ory & Mokhtarian, 2010) and factor analysis (Curran et al., 1996; Hutchinson & Olmos, 1998; Savalei, 2008), as well as IRT (Svetina et al., 2017; Woods, 2014). Researchers have found that., in IRT models, non-normality in the latent trait distribution can significantly decrease the accuracy of item and person parameter recovery. In the Maximum Likelihood Estimation (MLE) method, non-normality tends to produce biased estimates, especially at the tails of the distribution (Kieftenbeld & Natesan, 2012; Selçuk & Demir, 2024; Seong, 1990). However, in the Bayesian framework, Maximum a Posteriori (MAP), Expected a Posteriori (EAP), and Markov chain Monte Carlo (MCMC) methods can partially mitigate non-normality by incorporating the sample’s prior distribution, but their performance is still impacted by prior misspecification when the sample size is insufficient to address non-normality (Finch & Edwards, 2016; Kieftenbeld & Natesan, 2012; Selçuk & Demir, 2024). Additionally, Sass et al. (2012) addressed that non-normal latent distributions can distort item difficulty and discrimination estimates, affecting person ability estimates across all methods.

Although a few studies have examined the impact of non-normality of latent trait under unidimensional and multidimensional IRT models, the impact on estimating parameters of bifactor IRT model remains unstudied. Bifactor models are unique in terms of their orthogonal structure of general and specific factors. When the latent distributions are non-normal, the orthogonality assumption may no longer be appropriate or realistic. For instance, a skewed general trait and symmetric specifics can confound the source of variance. Bonifay and his colleagues (2017) noted that bifactor models are highly sensitive to data features like skewness or limited variability. Moreover, bifactor models estimate general and specific latent attributes simultaneously, assuming normal latent trait distribution for both factors. The violation of the normality assumption from either general or specific factors possibly impacts the estimation of both factors.

Previous IRT simulation studies typically imposed non-normality (e.g., skewness or kurtosis) only on the general latent attributes, assuming specific factors a normal distribution (e.g., Wang et al., 2018). However, in bifactor models, specific factors also influence item responses and are estimated simultaneously alongside the general factor. The violation of normality in specific factors can still distort parameter estimates (Bonifay, Lane, & Reise, 2017). Moreover, interaction effects between non-normal general and specific factors remain underexplored in existing literature, leaving a critical gap in our understanding of bifactor estimation robustness.

In addition, MAP estimation has demonstrated superior performance over ML under conditions of latent trait non-normality, producing lower bias and root mean square error (RMSE) in both item and person parameter estimates (Wang et al., 2018; Kieftenbeld & Natesan, 2012). However, Bayesian estimation methods (e.g., MAP and EAP) rely on informative priors, small sample size may not sufficiently adjust for skewed latent attribute distributions, while each specific factor, with even smaller item could face more severe impact.

Finally, simulation studies frequently constrain non-normality to a fixed level, typically skewness of 2.0 and kurtosis of 7.0 (Wang et al., 2018). While realistic in some applied contexts, this design choice restricts a gradient-based examination of robustness, limiting our understanding of how varying degrees of non-normality influence estimation accuracy.

The goal of this paper is to examine the impact of non-normal latent trait distributions, both in general and specific factors, on parameter estimation in bifactor IRT models. Through a simulation study, this research investigates how varying degrees and combinations of skewness and kurtosis in both general and specific traits affect the recovery of item and person parameters. Additionally, the study compares the performance of Maximum Likelihood (ML) and Maximum a Posteriori (MAP) under different conditions of non-normality. By addressing the often-overlooked influence of non-normality in specific factors and exploring interaction effects between non-normal general and specific traits, this paper aims to inform the robustness and practical implications of bifactor IRT modeling in applied assessment contexts.

**Bifactor Grade Response Model**

The Bifactor-GRM (Gibbons et al., 2007; Reise et al., 2010) is an extension of the conventional GRM (Samejima, 1969) and is suitable for handling ordinal response data. Suppose a test involves one general factor and S specific factors and each item is related to the general factor and one of the S specific factors (Toland et al., 2017). Assume item *j* is associated with a general factor *g* and a specific factor *s*, and responses to item *j* is polytomous with ordered categorical values of 1, …, *K*. The cumulative probability that a respondent *i*’s response falls at or above a particular ordered category, given latent trait *θ*, can be formulated as:

 (1)

in which, *θg* represents the respondents’ latent trait on the general factor, while *θs* denotes their latent trait on the specific factor. The parameters *ajg* and *ajs* are the discrimination of item *j* on the general and specific factors, respectively, and *bjk* is the threshold for category *k*. The constant *D* is added as a scaling factor, typically set to 1 or 1.7.

Based on Equation (1), the category response functions, which indicate the probability of responding to a particular category given *θ*, can be calculated by subtraction of adjacent boundary functions,

 (2)

in which,  and are two adjacent cumulative probabilities.

**Simulation Study**

**Design Factors**

This study conducts a Monte Carlo simulation to assess the impacts of non-normality issue on both factor and specific factor within a bifactor model. Additionally, the research incorporates four-category polytomous items, which are frequently used in psychometric and educational assessments. Drawing on methodologies established in prior studies (Auné, 2020; Mao, 2022; Rijmen, 2011; Svetina et al., 2017; Wang et al., 2018), this study will summarize common and practical non-normality issues and explore how deviations from normality can affect bifactor model parameters estimation To observe this, a total of five variables were manipulated, as shown in Table 1.

**Table 1.**

*Simulation Design*

|  |  |  |
| --- | --- | --- |
| **Design factors** | **Levels** | **Values of Levels** |
| Sample size (*N*) | 3 | *N* = 250, 500, 1000 |
| Number of Item per Factor (*Is*) | 3 | *Is* = 5, 10, 20 |
| Number of Specific Factor (*Fs*) | 2 | *Fs* = 2, 4 |
| Non-normality on general factor (*Normg*) | 2 | Normal : Skew = 0, Kurt = 0,  Non-normal : Skew = 2, Kurt = 7 |
| Non-normality on specific factor (*Norms*) | 2 | Normal : Skew = 0, Kurt = 0,  Non-normal : Skew = 2, Kurt = 7 |

The sample size has three levels (*N* = 250, 500, 1000), the number of items per factor has three levels (*Is* = 5, 10, 20), and specific factor has two levels (*Fs* = 2, 4). Our study simulates conditions of non-normality for both the general factor (*Normg* = Normal, Non-normal) and the specific factor (*Norms* = Normal, Non-normal). The normal condition is characterized by a skewness of 0 and a kurtosis of 0, while the non-normal condition is characterized by a skewness of 2 and a kurtosis of 7, both of which were commonly adopted in previous research (Curran et al., 1996; Wang et al., 2018). For each condition, we set all specific factors fixed at same level of skewness and kurtosis.

The experimental design comprehensively intersects these manipulated variables, generating 72 unique simulation conditions. Each condition underwent 1000 replications through the "SimMultiCorrData" package in R (Fialkowski, 2018), ensuring robust and detailed analysis of the bifactor model's performance under varying degrees of non-normality.

**Item parameter**

In psychological and psychiatric research, the general factor discrimination parameters are usually positive and fall within the range of 1.1 to 2.8 (Atkinson, 2018; Auné, 2020; Berkeljon, 2012; Raines, 2015). Previous studies have consistently shown that specific factor discrimination parameters are typically smaller than those of the general factor, generally ranging from 0 to 1.5 (Wang et al., 2018). Given the assumption of orthogonality of the latent traits on the general factor and specific factor, we generated two sets of latent trait for each factor, separately. The discrimination parameter for the general factor is randomly set to range from 1.1 to 2.8, while the discrimination parameter for the specific factors are kept within the range of 0 to 1.5.

Although item difficulty values can theoretically range from negative infinity to positive infinity, they practically locate from -2 to +2 (Hambleton, 1993; Hambleton & Swaminathan, 1985). Psychological and psychiatric assessments often use a four-point Likert scale to measure latent traits or personalities (Auné et al., 2020; Rijmen,2011). Building on the setting in Wang’s (2018) prior research, this study generated normally distributed item thresholds / locations following three intervals: b1[−2, −0.67], b2[−0.67, 0.67], and b3[0.67, 2], to distinguish the possibilities of choosing each response category.

**Person parameter**

The values for skewness between -2 and +2 are considered acceptable for assuming normality (George & Mallery, 2010). Additionally, kurtosis is another critical indicator of distribution sharp, and values located between -7 to +7 are generally considered as normality (Hair et al., 2010; Bryne, 2010). Therefore, we simulate two levels of non-normality, normality (skewness: 0, kurtosis: 0), and non-normality (skewness: 2, kurtosis: 7). There were four combinations of normality conditions across the general factor and specific factor, reflecting whether each was normal or non-normal respectively. In this study, we employed the Fleishman method to generate nonnormal distributions, involving manipulating a normally distributed random variable using a cubic polynomial, thereby adjusting skewness and kurtosis through modification of the polynomial's coefficients (Fleishman, 1978). All latent traits on specific factors (θs) are set equally.

**Estimation**

The item parameters in this study were estimated using the "bfactor()" function from the R package "mirt". Due to complex and non-normal data structures, the study increase the iteration limit to 6000 to ensure accurate parameter recovery. For estimating the person ability parameters, two estimation methods, namely, maximum a posteriori (MAP) and maximum likelihood (ML), were utilized. Within the R package "mirt," the estimation on person ability parameters involved utilizing the "fscores()" function. It is important to note that, in “mirt” package, the threshold (location) parameters are outputted as *djk* such that *bjk* = *-djk*, where *bjk* refers to the threshold used in in Equation 1.

***Evaluation criteria***

The accuracy of parameter recovery in this study is assessed through the calculation of bias, root mean squared error (RMSE), and Pearson correlations (only for person ability). These measures are calculated for both item and person parameters. The item parameters include two discrimination parameters for general factor and specific factor as well as three threshold parameters. The person parameters consist of two latent traits corresponding to general and specific factors.

**Bias.** The relative bias is estimated for all the parameters of model, including item parameters (ag, as, c1, c2, c3) and personal parameter (θg, θs) as,

 (3)

where is the estimated parameters () across valid replications and is the true parameters (). In the and , *j* represents the item number, ranging from 1 to J. The total number of items J is computed by multiplying the number of items in each specific factor by the number of specific factors. For each condition, a total of 1000 replications are carried out, denoted as R in equation (3).

**RMSE**. The RMSE is estimated for all the parameters of model, including item parameter (ag, as, c1, c2, c3) and personal parameter (θg, θs) as,

 (4)

where refers to the same as mentioned equation (3).

To determine the effect of the design factors on the outcome variables, we conducted a factorial analysis of variance (ANOVA) with effect size (*η2*) computed to gauge the contribution of all the design factors and their interaction. Note that only the practically significant design factors and their interactions are considered as salient effect based on J. Cohen’s (2013) small effect size of 0.01, moderate effect size of 0.06, and large effect size of 0.14.

**Results**

**Item Parameter Estimation**

In this section, we only looked at ANOVA effect size (*η²*) exceeding 0.06, to get a clear picture of how non-normality and other design factors affected estimating item parameters for bias and RMSE.

**Table 2**

*Generalized Eta Squared (η²)* *for Item Parameter Estimates*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Source of Variation |  | Bias |  |  | RMSE |  |
| *ag* | *as* | *c* | *ag* | *as* | *c* |
| *Normg* | .498 |  | .167 |  |  |  |
| *Is* |  |  |  | .098 | .199 | .115 |
| *N* | .064 |  |  | .109 | .136 | .282 |
| *Is× N* |  |  |  |  | .082 |  |

***Note.*** *Normg*: Non-normal distributed general-factor latent trait; *Is*: Item number per specific factor; *N*: Sample size; *Is× N*: Interaction between *Is* and *N*;*ag*: discrimination of the general factor; *as*: average discrimination of specific factors; *c*: average value of thresholds or locations (*c1*, *c2*, and *c3*).

According to Table 2, non-normality in the general factor (*Normg*) primarily affected the bias in estimating discrimination of general factor (*ag*) and thresholds or locations (*c*), with *η²* = 0.498 and 0.167, respectively. Regarding RMSE, *Normg* had a negligible effect on all item parameter estimations, while item number per specific factor (*Is*) and sample size (*N*) had a significant influence. Additionally, the only interaction between *Is* and *N* (0.082) had an effect size over the threshold, significantly influencing RMSE of estimating the discrimination on specific factors (*as*). We will apply a plot to explain this interaction effect in the following section.

**Table 3**

*Means and SDs of Bias and RMSE in Item Parameter Estimation Across Different Conditions*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Variable and Condition | | *ag* | *as* | *c1* | *c2* | *c3* |
| **Bias** |  |  |  |  |  |  |
| *Normg* | Normal | **0.03(0.28)** | -0.01(0.30) | **-0.03(0.23)** | **-0.01(0.19)** | **0.01(0.23)** |
|  | Non-normal | **-0.19(0.29)** | 0.00(0.32) | **-0.10(0.24)** | **-0.10(0.18)** | **-0.07(0.21)** |
| *Is* | 5 | -0.04(0.56) | 0.04(0.69) | -0.12(0.39) | -0.08(0.22) | -0.01(0.36) |
|  | 10 | -0.09(0.25) | -0.01(0.22) | -0.07(0.20) | -0.06(0.18) | -0.04(0.20) |
|  | 20 | -0.09(0.22) | -0.01(0.16) | -0.05(0.20) | -0.05(0.18) | -0.03(0.20) |
| *N* | 250 | **-0.05(0.42)** | 0.01(0.46) | -0.09(0.33) | -0.06(0.25) | -0.01(0.31) |
|  | 500 | **-0.09(0.24)** | -0.01(0.24) | -0.06(0.20) | -0.05(0.17) | -0.03(0.20) |
|  | 1000 | **-0.10(0.18)** | -0.02(0.14) | -0.06(0.14) | -0.06(0.13) | -0.04(0.14) |
| ***RMSE*** |  |  |  |  |  |  |
| *Normg* | Normal | 0.28(2.01) | 0.30(2.22) | 0.23(1.20) | 0.19(0.61) | 0.24(1.31) |
|  | Non-normal | 0.34(2.97) | 0.32(3.98) | 0.26(2.07) | 0.20(0.37) | 0.22(0.80) |
| *Is* | 5 | **0.57(4.26)** | **0.69(5.57)** | **0.41(2.90)** | **0.23(0.86)** | **0.36(1.85)** |
|  | 10 | **0.26(0.57)** | **0.22(0.52)** | **0.22(0.40)** | **0.19(0.26)** | **0.20(0.36)** |
|  | 20 | **0.23(0.30)** | **0.16(0.23)** | **0.21(0.28)** | **0.19(0.25)** | **0.20(0.26)** |
| *N* | 250 | **0.43(3.45)** | **0.46(4.51)** | **0.35(2.35)** | **0.25(0.70)** | **0.31(1.50)** |
|  | 500 | **0.26(0.50)** | **0.24(0.61)** | **0.21(0.42)** | **0.18(0.23)** | **0.20(0.37)** |
|  | 1000 | **0.20(0.28)** | **0.14(0.27)** | **0.15(0.21)** | **0.14(0.17)** | **0.14(0.19)** |

***Note.*** *Normg*: Non-normality on general factor; *Is*: Number of Item on specific factors; *N*: Sample size;*ag*: discrimination of general factor; *as*: average discrimination of specific factors; *c*: average value of thresholds or locations (*c1*, *c2*, and *c3*).

Table 3 presents all means and standard deviations (SDs) of bias and RMSE in estimating five item parameters (*ag*, *as*, *c1*, *c2*, *c3*) across all simulation conditions. Generally, the estimation biases of item parameters (*ag*, *c1*, *c2*, and *c3*) are less than or equal to zero when the general-factor ability is not normally distributed (Normg = non-normal). This addresses the fact that non-normality in the general factor can decrease accuracy in item parameter estimation. However, in this simulation study, non-normality on the general factor (Normg = Non-normal) does not have a big impact on RMSE of estimation for any of the five item parameters (*ag*, *as*, *c1*, *c2*, *c3*).

Also, as item number per specific factor (*Is*) go from 5 to 20, both bias and RMSE of estimation decrease, which suggests that having more items makes estimation more stable. Similarly, a sample size (*N*), increasing from 250 to 1000, also lowers bias and RMSE of estimation on all item parameters. Overall, the results suggest that non-normally distributed ability on the general factor, larger item sets, and bigger sample sizes all contribute to a better estimation accuracy.

**Figure 1**

*Interaction Effect on RMSE of Specific-factor Discrimination (as)*

A graph of a sample size and a sample size

Description automatically generated with medium confidence

***Note.*** *as*: specific-factor discrimination; RMSE: Root Mean Square Error; Normality on general factor is depicted by the solid line, while non-normality on general factor is depicted by the dashed line.

Figure 1 shows that the RMSE for estimating the specific-factor discrimination parameter (*αs*) decreases as both the sample size and the number of items per specific factor increase. The existence of non-normality on general-factor latent ability (*θg*) had little impact on RMSE of estimating specific-factor discrimination (*αs*). Additionally, increasing sample size and the item number per specific factor significantly improves the accuracy of specific-factor discrimination (*αs*) estimation, as measured by RMSE.

**Person Parameter Estimation**

**Table 4**

*Generalized Eta Squared (**η2) for Person Parameter Estimates*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Source of Variation | Bias | | RMSE | | |
| *θg* | *θs* |  | *θg* | *θs* |
| *Normg* | **.163** | .003 |  | .039 | **.082** |
| *SF* | .001 | .047 |  | .009 | .038 |
| *Fs* | .004 | .036 |  | **.539** | **.657** |
| *Is* | .012 | **.092** |  | **.742** | **.880** |
| *N* | .002 | .000 |  | .005 | .016 |
| *Method* | .042 | .020 |  | **.856** | **.967** |
| *SF× Is* | .000 | .004 |  | **.117** | **.168** |
| *Is× N* | .000 | .002 |  | .041 | .014 |
| *Is× Normg* | .004 | **.091** |  | .002 | .005 |
| *Fs× Method* | .000 | .028 |  | **.264** | **.179** |
| *Is× Method* | .001 | **.093** |  | **.589** | **.826** |
| *Normg × Method* | .031 | .000 |  | .006 | **.074** |
| *Fs× N× Normg* | .000 | .001 |  | .001 | .009 |
| *Is× N× SF* | .004 | .002 |  | **.072** | .011 |
| *Fs× Is× Method* | .001 | .004 |  | **.079** | **.085** |
| *Is× Normg × Method* | .003 | **.093** |  | .001 | .005 |
| *Fs× Is× N× Normg* | .003 | .003 |  | .011 | .029 |
| *Fs: Is: N: Normg: Norms* | .001 | .001 |  | .049 | .003 |

***Note.*** *Normg*: Non-normality of the general factor; *SF*: Non-normality of the specific factor; *Fs*: Number of specific factors; *Is*: item number per specific factor ; *N*: Sample size; *Method*: Person parameter estimation algorithm (MAP or ML); *θg*: Estimated general-factor ability; *θs*: Estimated specific-factor ability. Interactive effects are noted by multiplication sign (*×*).

Table 4 reveals several critical insights in examining the influence of non-normality, integrated by number of specific factors (*Fs*), the item number per specific factor (*Is*), sample size (*N*), and the algorithm for person parameter estimation (*Method*). In terms of bias, general-factor non-normality (*Normg*) accounted for a substantial proportion of variance in general-factor ability (*θg*) estimation (*η2* = .163), while *Is* accounted for a smaller proportion of variance in specific-factor ability (*θs*) estimation (*η2* = .092). Regarding RMSE, we can find more meaningful impacts. Specifically, the estimation algorithm had the largest effect on both *θg* and *θs*, with *η2* values of .856 and .967, respectively. This highlights the critical importance of choosing algorithm between MAP and ML for enhancing accuracy of person parameter recovery.

Table 4 also reveals interaction effects, but we only discuss two-way interactions here and leave three-way interactions discussed and plotted in the next section. There were only two two-way interactions found to influence specific-factor ability (*θs*) with respect to bias. These were the interaction between the number of items per specific factor (*Is*) and general-factor non-normality (*Normg*), and the interaction between *Is* and the estimation method (*Method*). Regarding RMSE, several two-way interactions accounted for variance in both *θg* and *θs*. For *θg*, three two-way interactions were found, the interaction between specific-factor non-normality and the number of items per specific factor (*SF× Is*, *η2* = .117), the number of specific factors and estimation method (*Fs× Method*, *η2* = .264), and non-normality of the specific factor and estimation method (*Is× Method*, *η2* = .589). Meanwhile, for *θs*, four two-way interactions were addressed, the interaction between specific-factor non-normality and the number of items per specific factor (*SF× Is*, *η2* = .168), the number of specific factors and estimation method (*Fs× Method*, *η2* = .179), non-normality of the specific factor and estimation method (*Is× Method*, *η2* = .826), and non-normality of the general factor and estimation method (*Normg× Method*, *η2* = .074). Although the main effect of specific-factor non-normality (*SF*) was not statistically significant, SF was a key component in several significant two-way interaction effects. The main effect of general-factor non-normality (*Normg*), however, was comparatively small.

In conclusion, general-factor non-normality (*Normg*) had a substantial impact on bias in *θg* estimation, while only *Is* had a smaller but notable role in specific-factor ability *θs* estimation. Notably, the choice of estimation algorithm (MAP or ML) was the most influential factor, significantly affecting both *θg* and *θs* in terms of RMSE. In several identified two-way interactions, *Is* and the estimation method pronounced major effects on RMSE, and bias of *θs* estimation. Unexpectedly, sample size (*N*) exhibited minor impact in both one-way and two-way interactions. These findings underscore that, to enhance person parameter recovery, researchers should carefully select estimation algorithm, specific-factor number and item number, when the Bifactor-GRM has non-normality issue on either general or specific factor.

**Table 5**

*Bias and RMSE in Person Parameter Estimation Across Different Conditions*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Variable and Condition | | Bias | | RMSE | | |
| *θg* | *θs* | | *θg* | *θs* |
| *Normg* | Normal | 0.00(0.06) | 0.01(0.06) | | 0.50(0.32) | 1.07(0.67) |
|  | Non-N | 0.05(0.06) | 0.00(0.08) | | 0.53(0.33) | 1.01(0.63) |
| *Norms* | Normal | 0.03(0.06) | -.01(0.07) | | 0.52(0.34) | 1.02(0.65) |
|  | Non-N | 0.02(0.06) | 0.02(0.07) | | 0.51(0.32) | 1.06(0.65) |
| *Fs* | 2 | 0.03(0.06) | 0.00(0.08) | | 0.61(0.38) | 1.17(0.70) |
|  | 4 | 0.02(0.06) | 0.02(0.07) | | 0.42(0.23) | 0.90(0.56) |
| *Is* | 5 | 0.03(0.06) | -.02(0.09) | | 0.71(0.42) | 1.37(0.84) |
|  | 10 | 0.02(0.06) | 0.01(0.06) | | 0.48(0.23) | 1.01(0.52) |
|  | 20 | 0.02(0.06) | 0.02(0.05) | | 0.35(0.14) | 0.74(0.31) |
| *N* | 250 | 0.02(0.07) | 0.01(0.08) | | 0.51(0.30) | 1.02(0.63) |
|  | 500 | 0.02(0.06) | 0.01(0.07) | | 0.52(0.34) | 1.05(0.66) |
|  | 1000 | 0.03(0.05) | 0.00(0.06) | | 0.52(0.33) | 1.04(0.66) |
| *Method* | MAP | 0.01(0.05) | 0.00(0.03) | | 0.30(0.07) | 0.52(0.11) |
|  | ML | 0.04(0.06) | 0.01(0.10) | | 0.73(0.34) | 1.56(0.54) |

***Note.*** The table displays means and standard deviations (SDs, in parentheses) of bias and RMSE under various conditions in person parameter estimation. *Normg*: Non-normality of the general factor; *Norms*: Non-normality of the specific factor; *Fs*: Number of specific factors; *Is*: Item number per specific factor ; *N*: Sample size; *Method*: Person parameter estimation method (MAP or ML); *θg*: Estimated general-factor ability; *θs*: Estimated specific-factor ability.

In Table 5, the person’s general-factor trait/ability(*θg*) shows small bias across all conditions, with non-normal distribution conditions on general factor showing the most significant bias (0.05), compared to normal distribution condition (0.00). Another notable difference is that ML method exhibits higher bias (0.04) than MAP method (0.01), indicating the MAP method has better performance on estimating *θg*. Meanwhile, the biases of persons’ specific-factor traits/abilities(*θs*) are generally close to zero across all conditions, meaning that estimated *θs* are closed to real *θs* or symmetrically distributed around real *θs*.

Regarding RMSE, the *θg* consistently exhibited lower RMSE compared to *θs* across all conditions. Also, the non-normality issue on the general factor (*Normg* = Non-normal) affected estimation on *θg* slightly, increasing only marginally from normal distribution (0.50) to non-normal distribution (0.53). However, non-normality on the general factor did not increase RMSE of estimation on *θs*, even causing decreasing from 1.07 to 1.01. Conversely, the non-normality issue on the specific factor (*Norms* = Non-normal) increased RMSE of estimation on *θs* from 1.02 to 1.06, while decreasing RMSE of *θg* from 0.52 to 0.51. Additionally, higher number of specific factors (*Fs*) and item number per specific factor (*Is*) are significantly decrease the RMSE of estimation on both *θg* and *θs*. The most important factor is method, the MAP method has smaller RMSE on both *θg* (0.30) and *θs* (0.52), compared to the ML method for estimating *θg* (0.73) and *θs* (1.56). This result indicates that the MAP method is a better performance on ability estimation.

**Figure 2**

*Bias of Person General-factor Ability (𝜃g) Estimation*A graph of a number of items

Description automatically generated with medium confidence

***Note.*** MAP: The Maximum A Posteriori estimation; ML: the Maximum Likelihood estimation. Normality on general factor is depicted by the solid line, while non-normality on general factor is depicted by the dashed line.

Figure 2 addresses the impact of non-normal distribution existing on estimating general-factor ability, and compares the performance of MAP or ML methods. When using the MAP method, both normal (solid line) and non-normal (dashed line) distributions of general-factor ability result in minimal bias, which remains stable across varying numbers of items per specific item. In contrast, while the ML method also shows low bias in estimating general-factor ability, it exhibits a noticeable increase in bias as the number of items grows, from negative to positive, suggesting that ML is more sensitive to non-normal distribution of general-factor ability.

Overall, the results demonstrate that MAP provides more stable estimates under different distributional assumptions, whereas ML can become significantly biased in the presence of non-normality. Specifically, smaller numbers of items per specific factor led to notable negative bias, while larger numbers of items result in positive bias.

**Figure 3**

*RMSE of Person General-factor Ability (𝜃g) Estimation: interaction effect of Sample Size, Item Number, and Non-normality on Specific Factor*

A graph of different sizes and sizes of items

Description automatically generated with medium confidence

***Note.*** Normality on general factor is depicted by the solid line, while non-normality on general factor is depicted by the dashed line.

Figure 3 compares the RMSE in general-factor ability (*𝜃g*) estimation across sample size, item number per specific factor (*Is*), and non-normality on specific factor (*Norms*). Overall, only item number per specific factor had a noticeable effect on RMSE of person general-factor ability (*𝜃g*) estimation. This means that greater items number per specific factor can significantly enhance the accuracy of estimating general-factor ability.

**Figure 4**

*RMSE of Person General-factor Ability (𝜃g) Estimation: interaction effect of Method, Item Number, and Specific Factor Number*

A graph of a number of items

Description automatically generated with medium confidence

***Note.*** MAP: The Maximum A Posteriori estimation; ML: the Maximum Likelihood estimation. The two specific factors condition is depicted by the solid line, while the four specific factors condition is depicted by the dashed line.

Figure 4 compares the RMSE in general-factor ability (*𝜃g*) estimation across methods, item number per specific factor (*Is*), and specific factor number (*Fs*). The result shows that the MAP algorithm generally has lower and more consistent RMSE values across all conditions of item numbers, outperforming the ML method. Under the ML method, raising *Fs* and *Is* can effectively reduce the RMSE; however, this impact is slight under the MAP method. In conclusion, increasing the number of items per specific factor and/or specific factor number in Bifactor-GRM can significantly reduce the estimation performance inequality between the MAP and ML approaches.

**Figure 5**

*RMSE of Person General-factor Ability (𝜃s) Estimation: interaction effect of Method, Item Number, and Specific Factor Number*

A graph of a number of items

Description automatically generated with medium confidence

***Note.*** MAP: The Maximum A Posteriori estimation; ML: the Maximum Likelihood estimation. The two specific factors condition is depicted by the solid line, while the four specific factors condition is depicted by the dashed line.

Figure 5 addressed the RMSE in specific-factor ability (*𝜃s*) estimation across methods, item number per specific factor (*Is*), and specific factor numbers (*Fs*). Similar to the RMSE in general-factor ability (*𝜃g*) estimation, the MAP method outperforms the ML method. Both methods show that increasing *Fs* and *Is* lead to a reduction in RMSE under the MAP method. Additionally, the ML method exhibits extremely high RMSE, particularly under conditions with a low number of items per specific factor. This indicates that specific-factor ability (*𝜃s*) estimation is more sensitive to a small number of items within each specific factor.

**Discussions**

The non-normality in latent ability/trait distributions is a common psychological and educational assessment. As a frequently used model, the bifactor graded response model (Bifactor-GRM) might face a more complicated estimation problem when a non-normal distribution can happen on both the general factor and the specific factor. This section will address violations of the normality assumption in both item and person parameter estimation within the Bifactor-GRM and offer implications for both researchers and practitioners in psychometric areas.

Our results revealed that non-normality in the general factor predominantly influenced the bias in estimating the discrimination on the general factor (*ag*) and, to a lesser extent, the location parameters (*c1*, *c2*, and *c3*). In detail, general-factor non-normality resulted in increased negative bias in the discrimination parameter (*ag*) estimation. Regarding RMSE, general-factor non-normality has an ignorable impact on discrimination estimation both on general and specific factors, as well as location. However, the number of items per specific factor (*Is*) and sample size (*N*) have significantly influenced the result. This indicates that although non-normality may induce bias, increasing the number of items and the sample size can enhance the accuracy of item parameter estimations. The interaction between *Is* and *N* further emphasizes the significance of sample size concerns when addressing a fluctuating number of items per factor.

In our research, we used the two estimation algorithms, MAP and ML, to estimate the person parameter in Bifactor-GRM. The result exhibited that the MAP algorithm generally outperformed the ML algorithm in terms of both bias and RMSE for estimating general-factor and specific-factor abilities (*θg* and *θs*), especially for estimating specific-factor abilities (*θs*), if the number of items per specific factor is small. This suggests that MAP provides more reliable and accurate assessments, even with a limited number of items and a small sample size, while ML needs a sufficient number of items to get accurate person parameter estimates. Interestingly, while general-factor non-normality had a notable impact on the bias of a person’s general-factor ability estimates, its effect on the RMSE was relatively small. This suggests that while non-normality can shift the estimated values, it does not necessarily lead to a substantial increase in the variability of the estimates.

**Implications**

According to the results, there are several important implications for psychological and educational applications. To adopt the Bifactor-GRM, researchers and practitioners must acknowledge the skewness and kurtosis on both general- and specific-factor abilities possibly causing inaccuracy on item parameter recovery. Secondly, our findinNorms strongly advocate for the use of MAP estimation in the recovery of person parameters, particularly when the number of items per specific factor is limited, especially less than 10 items. The outstanding performance of the MAP algorithm for estimating person parameters indicates that it is a more robust method for addressing the issue caused by non-normality and limited data. Third, increasing the sample size and the number of items per specific factor could make the estimates of both item and person parameters more accurate, which would lessen the negative effects of non-normality.

**Limitations**

This study definitely has certain drawbacks which require additional research. During the simulation design phase, we exclusively simulated only one type of non-normality, namely skewness and kurtosis, and defined a fixed combination of their values. To enhance understanding of complex non-normality issues in real-world data, we may incorporate additional types of non-normality (e.g., bimodality) and utilize various combinations of skewness and kurtosis values. Furthermore, we exclusively examined constrained design factors of simulation study. Additional factors, like the number of factor loadings and the correlation between specific factors, could influence parameter recovery as well. Moreover, our research employed simulated data, which might limit the applicability of our results to real-world scenarios. Future research should examine the performance of the Bifactor-GRM in non-normal conditions using empirical data. Finally, we were able to evaluate the efficacy of psychometric software and R packages (e.g., FlexMirt, Mplus, and the R package lavaan) in Bifactor-GRM parameter recovery.

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