**The IRT Approach to Measurement Equivalence**

Item response theory (IRT) is an alternative to classical test theory (CTT). Unlike CTT, whose analysis unit is the whole test (Hambleton, Swaminathan, & Rogers, 1991), IRT focuses on individual item responses and connecting them with the latent trait measured by the test (Drasgow & Hulin, 1990).

There are two major types of IRT models, one is the dominance model, and the other is the ideal point model. The 2PLM and Samejima’s Graded Response Model (SGRM) are two representative dominance models used to analyze dichotomous and polytomous personality measures, respectively. For the ideal point model, the General Graded Unfolding Model (GGUM; Roberts et al., 2000) has gained a lot of attention. The difference between the dominance model and the ideal point model lies in their assumptions about response processes. The dominance IRT methods, deriving from Likert’s 1932 rating scales development and analysis approach, assume that the higher the respondent’s trait level, the more likely she will answer positively (Drasgow et al., 2010). Whereas the ideal point methods, inspired by a series of Thurstone’s (1927, 1928, 1929) studies on measuring attitudes, hypothesize that the closer the statement is to a respondent’s trait level, the higher the probability of endorsement (Drasgow et al., 2010).

***The dominance IRT models: 2PLM and SGRM***

In personality tests, the 2-paramter logistic model (2PLM) and Samejima’s Graded Response model are two very widely used IRT models. The 2PLM is applicable to dichotomous responses, while SGRM deals with polytomous response data.

The item response function (IRF) for the 2PLM is:

*Pi (θ)* is the probability of a random respondent correctly answering Item *i* correctly. Since the responses are dichotomous, the probability of answering this item wrong then is given by:

There are two item parameters in a 2PLM. *ai*is the discrimination parameter that represents the degree to which an item separates latent trait levels that are close to each other (Maurer, Raju, & Collins, 1998). The larger *ai* is, the steeper the IRF. *bi*is the difficulty parameter. It is the point on the latent trait (θ) scale where the probability of a correct response is equal to 0.5. The larger the difficulty parameter, the harder the item. D is the scaling factor that makes the logistic function to resemble as close as possible to the normal ogive curve, and is usually set equal to 1.702 (Valbuena, 2003). Exp stands for an exponential function.

Samejima’s Graded Response Model (SGR; 1969) is and enhancement of the 2PLM (Kosinski, 1999) and one of the most popular polytomous models in personality research. Under SGR, a polytomous response is broken down to a series of binary response sets by boundary response function (BRF), which is obtained by gradually merging response options (Kosinski, 1999). The probability of selecting response option k equals the difference between the probability of endorsing response option kand any higher options and that of endorsing response option k+1 and any higher options. The probability of selecting option *k* on item *i* is given by:

*BRFi,k(θ)* is the boundary response function for option k on item i, and is calculated using 2PLM, so the item paramters (*ai*, *bi,k*)and scaling constant (*D*) used are the same as in 2PLM.

***The ideal point model: General Graded Unfolding Model (GGUM)***

The ideal point models are not as well developed as the dominance models, and among the few ideal point models, the most employed is the the General Graded Unfolding Model (GGUM; Roberts, Donoghue, & Laughlin, 2000), which is applicable to either binary or graded responses. As discussed above, ideal point models assume a response process different from dominance models, and GGUM, according to Roberts et al. (2000) developed GGUM based on four basic premise about the response process. The first premise is that an individual tends to agree with the item with trait level that’s close to her own trait level. The second premise is that a respondent disagrees with an item because the item trait level is either higher or lower than her own trait level. Similarly, a person closer to an item on the latent trait continuum can also agree with this item from either above or below. The third premise is that subjective responses (not observed responses) to attitude statements follow a cumulative item response model. The last premise is that an individual is equally likely to agree with an item located either h unites above or below her position on the attitude continuum. Developed from the four premises above, the formal definition of the GGUM is:

This function gives the probability associated with the *j*th respondent’s observable response to the *i*th item. *Zi* is the observable response to item *i*, and z ranges from 0 to C, with 0 standing for the strongest level of disagreement, and C standing for the strongest level of agreement. C equals the number of response options minus 1. M equals 2\*C+1, representing the number of subjective response categories minus 1. *αi* is the discrimination parameter, and *δi* is the location parameter of item i on the latent trait continuum. *τik* is the location of the *k*th subjective response category threshold on the theta continuum relative to the location of the *i*th item. The *τik*s are symmetric about the point (*θj* - *δi*) = 0.

***Data-model fit***

The dominance models are predominant in scale development and analysis, but generally work the best only in the context of cognitive ability testing (Chernyshenko, Stark, Chan, Drasgow, & Williams, 2001), because this domain is where a respondent’s capacity or maximum performance capability is pitted against the extremity of difficulty of an item (Drasgow et al., 2010; Stark et al., 2006b). For example, in an ability test, a respondent with a high ability is expected to perform well because she is likely to dominate all the easy and moderately difficult items (i.e., getting them all correct), and get some of the hardest items correct.

However, when the studied field moves from ability to personality, the dominance models sometimes show inadequate fit. In fact, before Roberts et al. (2000) proposed the GGUM, several studies had already realized the unfolding property of some attitude statements (van Schuur & Kiers, 1994; Roberts, 1995; Andrich, 1996; Roberts, Laughlin, & Wedell, 1999), which is different from the single-peaked response function of dominance IRT models. In 2001, one year after the GGUM was developed, Chernyshenko, Stark, Chan, Drasgow, and Williams fitted a variety of IRT dominance models (2PLM, 3PLM, and SGRM) to data from Goldberg’s Big Five Factor Markers (Goldberg, 1997, 1998), and the 16PF (Conn & Rieke, 1994). To their surprise, all of the dominance IRT models showed misfit, and the chi-square fit statistics obtained were generally larger than those of cognitive ability tests. This is probably because that in personality tests, a different response process is applied which requires introspection (Chernyshenko, Stark, Drasgow, & Roberts, 2007). When people are considering personality items, they ask themselves “Does this statement closely describe me?” Therefore, the maximum probability of endorsement is achieved only when the item trait level matches the individual’s trait level, and the probability of endorsement decreases as the distance increases between the item and individual’s trait levels (Drasgow et al., 2010). This is the “unfolding technique” described by Coombs (1964), who was also the one that coined the phrase “ideal point”. The unfolding property of items were proved by applying Levine’s (1984) maximum likelihood formula score model (MFSM). MFSM is a nonparametric IRT model, so it does not require an item to be logistic or monotonic to fit. It turned out that for item doubles and triples, MFSM showed better fit than the two logistic models, and more importantly, some of the items also violated monotonicity, the hallmark of dominance models (Levine, 1984; Drasgow et al., 2010). Stark et al. (2006b) compared fitting of two ideal point models (GGUM and MSFM) with that of two dominance models (2PLM and MSFM with a dominance constraints) to data of 16PF (Conn & Reike, 1994), and concluded that ideal point models can fit personality items as good or better than dominance models, because they are able to fit both monotonic and non-monotonic items, the latter of which dominance models can’t seem to handle well.

But the conclusion that in personality test, the ideal point model has better fit than the dominance model is not completely consistent across studies. Kosinski (2009) applied polytomous GGUM and SGRM to the Extraversion scale from the Goldberg’s 100-item Big Five personality questionnaire (Goldberg et al., 2006), and found that GGUM had worse model-data fit than SGRM. Attempts to improve the fit by removing poor fit items were successful for SGRM but not for GGUM. Broadfoot (2008) showed that GGUM had comparable fit with a partial credited model for conscientiousness and agreeableness data. Speer et al. (2016) fitted SGRM and GGUM to both both monotonic and non-monotonic conscientiousness and extraversion scales. GGUM and SGRM fitted almost equally well for item singles, but SGRM surpassed GGUM for items doubles and triples for all types of scales, even the non-monotonic scales. GGUM was also found to have fitted worse than SGRM when there’s no intermediate items on the scale, and GGUM didn’t show significantly better model-data fit than SGRM until 50% of all items on the test were carefully selected, good intermediate items (i.e., items that have high α and close-to-zero δ under GGUM and low a-parameters under SGRM; Cao, Drasgow, & Cho, 2014). It seems that relative model-data fit has a lot to do with the number and strength of the non-monotonic, or intermediate items.

Given the inconsistent results on comparison of applying to personality tests the dominance and ideal point IRT models, as well as the seeming appropriateness of the application, in the current study, we adopted both types of models. To be more specific, we chose the 2PLM and SGRM for the dominance IRT model, and polytomous and dichotomous GGUM for the ideal point model.

***DIF detection in the IRT framework***

In the current study, we utilized two paradigms to study DIF. Theses two diagrams are: (a) the null hypothesis significance testing (NHST) paradigm, and (b) the DIF effect size paradigm.

The NHST paradigm is the most popular approach to studying DIF. Under this paradigm, a null model and an alternative model are constructed and compared, and if the test statistic computed is statistically significant, then the studied item is considered a DIF item (Wang, Tay, & Drasgow, 2013). We used two approaches to build the models: (a) the constrained baseline model, and (b) the free baseline model. We also chose the log-likelihood ratio (LR) as the test statistic for model comparison, because the LR test was shown to have yielded the best results in general (Wang et al., 2013).

***The Constrained Baseline Approach.*** The null model is constructed by constraining the paramters of all items to be equal across groups. A series alternative models are then constructed by freeing one item at a time. All alternative models are compared with the null model by comparing the log-likelihood, and the item truly has DIF when the alternative model has the greater log-likelihood and the difference of log-likelihood chi-square statistics exceeds a critical value (Wang et al., 2013). If an item is considered free of DIF under the constrained baseline approach, then it’s safe to say that the item is a true DIF-free item, due to the inflated Type I error rate of the approach (Stark, Chernyshenko, & Drasgow, 2006a). Such an item should be used as a linking item in the free baseline approach, given the fact that the measures in the current study are short ones containing 20 items each (Rivas, Stark, & Chernyshenko, 2009).

***The Free Baseline Approach.*** The free baseline approach should be applied after the constrained baseline model has figured out the linking items, because of its close-to-nominal Type I error rate (0.05) and high power with sample sizes as small as 250 (Rivas et al., 2009). Contrast to the constrained baseline approach, the free baseline model has a null model where the paramters of all items across groups are allowed to be freely estimated, except for those of the linking items obtained through the constrained baseline approach. This model is constructed under the assumption that all non-linking items have DIF. Then a series of alternative models are constructed where non-linking items are constrained one at time, based on the assumption that the studied item has no DIF (Wang et al., 2013). The log-likelihood chi-square statistics are also obtained for model comparison, and an item has DIF if the log-likelihood of the null model is significantly greater than that of the alternative.

***The Log-likelihood Ratio Test.*** The LR test has been shown to be a good testing method for model comparison. In previous studies, the LR test was found to have high power for DIF detection (Wang, 2004; Stark et al., 2006a) and yield better results in general, compared with other test methods such as the Akaike information criterion [AIC], and Lord’s chi-square (Wang et al., 2013). Therefore, in the current study, we adopted the LR test method for DIF detection.

***DIF Effect Size.*** Although long has been the most widely used and accepted test for hypothesis, NHST is believed to be limited and flawed. For example, NHST is thought to be trivial because the null hypothesis can always be shown to be false to some extent (Cohen, 1990), because an effect an always be found if measured accurately enough (Nye, 2011). Also, NHST is criticized for using a cutoff value to turn a continuum into a dichotomous reject/do not reject decision (Kirk, 2006; Nye, 2011). Another major limitation of NHST is that it provides little information on the magnitude, value, or importance of an effect (Kirk, 2006). It is possible that statistically significant DIF is having negligible effect size, especially when the sample size is large. LaPalme and colleagues (2016) found that the DIF analysis showed that 13 of 16 items contained significant DIF, while according to DIF effect size, 10 out of the 16 items had DIF that’s too small to be meaningful (i.e., <.02; Cohen, 1992).

In order to obtain more accurate information on measurement non-equivalence, we included DIF effect size approach based on Nye (2011) in the current study. Nye’s DIF effect size first computed the squared difference of between conditional expected scores (Wang et al., 2013), and then divide it by the pooled standard deviation of item *i* in the two groups (Nye, 2011). The second step put the area difference on the standardized metric comparable to other effect size measures like Cohen’s *d*, and thus the DIF effect size can be interpreted the same way as how Cohen’s *d* is interpreted (Nye, 2011). Nye’s (2011) DIF effect size is given by:

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where *fF(θ)* is the ability density of the focal group with the mean and variance estimated from the transformed **theta-hat** distribution (Nye, 2011).

**The Current Study**

The current study was designed to assess measurement equivalence of some facets of the Big Five Personality tests on the CPS with data collected from the U.S. and the mainland China.

Model-data fit was computed for the SGRM and the polytomous GGUM, and the reasons for misfit were explored by analyzing ICCs given by the two polytomous IRT models, as well the 2PLM and the dichotomous GGUM. The authors assessed DIF via the SGRM, the polytomous GGUM, and DIF effect size, in order to better understand the existence and effect of ME on the CPS acorss the U.S. and Chinese cultures.