SOI: 1.1/TAS DOI: 10.15863/TAS

International Scientific Journal

Theoretical & Applied Science

p-ISSN: 2308-4944 (print) **e-ISSN:** 2409-0085 (online)

Year: 2017 **Issue:** 04 **Volume:** 48

Published: 06.04.2017 **http://T-Science.org**

Ameneh Hosseini

researcher,

Alborz higher education institute,

Afghanistan

lostpardise@yahoo.com

SECTION 21. Pedagogy. Psychology. Innovations in the field of education.

A CONFIRMATORY SURVEY OF DIFFERENTIAL ITEM FUNCTIONING

Abstract: *For the development of comparable tests in international studies it is essential to examine Differential Item Functioning (DIF) by different demographic groups, in particular cultural and language groups. For the selection of test items it is important to analyze the extent to which items function differently across the sub-groups of students. For the past several years, interest has been demonstrated in the study of differential item functioning (DIF). DIF is investigated whenever one wants to identify items on which two groups of examinees, matched on a mea sure of an appropriate variable, do not perform the same. Motivation for studying DIF could stem from psychometric considerations or from broader issues having to do with pedagogical, social, or psychological questions. The purpose of this study is to help ensure that strategies for differential item functioning (DIF) detection for students with disabilities are appropriate and lead to meaningful results. We surveyed existing DIF studies for students with disabilities and describe them in terms of study design, statistical approach, sample characteristics, and DIF results. Based on descriptive and graphical summaries of previous DIF studies, we make recommendations for future studies of DIF for students with disabilities.*

Key words: *Differential Item Functioning (DIF), Measuring, Students with Disabilities.*

Language: *English*

Citation: Ameneh H (2017) A CONFIRMATORY SURVEY OF DIFFERENTIAL ITEM FUNCTIONING. ISJ Theoretical & Applied Science, 04 (48): 1-7.

Soi: http://s-o-i.org/1.1/TAS-04-48-1 ***Doi***: crossref https://dx.doi.org/10.15863/TAS.2017.04.48.1

Introduction

Differential item functioning (DIF) has generated great interest in language testing applications (see Holland & Wainer, 1993; Penfield & Camilli, 2007). Rezaee & Shabani mentioned that researchers believe that through the use of DIF detection methodologies, factors contributing to group differential performance could be revealed, items flagged for DIF could be discarded, and finally fairer decisions could be made (Pae, 2004a; Rezaee & Shabani, 2010). Differential item functioning (DIF) refers to group differences in performance on a test item that cannot be explained by group differences in the construct targeted by the item (Crocker & Algina, 1986; Clauser & Mazor, 1998). Test items are identified as exhibiting DIF when, after matching examinee groups by a measure of ability, the performance of one group is significantly higher than the other group, on average. When DIF is found to occur, it means that a test item is measuring traits or abilities that are secondary to the targeted ability. For students with disabilities, such secondary traits could be a test taker's ability to access the math content in a word problem or the ability to respond to a computer-delivered constructed response item with a keyboard, for example. For such students, opportunity to learn the content may also be considered a secondary trait. Secondary traits measured by items showing DIF may be relevant or irrelevant to the targeted ability. When test items measure secondary traits or abilities that are irrelevant to the intended measure for some groups, such items are considered biased. Item bias is one aspect of fairness in testing and test use (American Educational Research Association, American Psychological Association, & National Council on Measurement in Education (1999).To ensure test fairness, DIF statistical methodology is used to empirically identify items that are performing differently across focal and reference groups after matching examinees based on ability, and human judgment is used to decide whether an item showing DIF is biased based on its characteristics (Zieky, 1993; Zumbo, 1999). When an item shows moderate to high levels of DIF, the item is typically reviewed by content experts. In the test development stage, an item showing DIF may either remain as is, be revised, or be deleted from the item pool. While small sample sizes had limited the number of DIF studies for students with disabilities historically, recent changes have provided opportunities to conduct item-level analyses and to make judgments about fairness for more specific disability subgroups.

Significant of the Study

Identifying the causes of DIF is also important part to understand about the relative strength and weakness of the examinee groups on the different skills and abilities that the test items measure. Some possible sources for such trends may include item content, item type or format, item context, content and cognitive dimensions associated with items. It may be possible to gain considerable insight into the potential causes of DIF by considering the statistical evidence of item level DIF in light of such item attributes. Practically, items identified as showing substantial DIF are not necessarily deleted from future tests, but these items are among those that need to be carefully reviewed prior to any subsequent use. Holland & et al indicated that by the widespread concern over differential item functioning most standardized testing programs place considerable importance on issues equity and fairness. For many testing programs, DIF analyses are a routine component of general item analyses, and items with unacceptable DIF statistics may undergo extensive sensitivity review or be rejected from operational use. DIF analyses are undertaken to identify items that unfairly advantage one or more examinee subgroups. DIF analyses differ from studies in that the former attempt to control for the effects of subgroup differences in the ability being measured whereas the latter ignore such factors. Most DIF approaches are best considered as global in that the resulting statistic is an index that somehow combines information across all ability ranges and provides an omnibus examination. (Holland & Thayer, 1988). CDIF is rather unique since CDIF values add up to the total DTF, enabling the practitioners to examine the net effect of deleting one or more items from the test. Although the DFIT framework has shown to be an effective mechanism for detecting DIF and DTF in IRT-based tests/questionnaires in several studies (e.g., Flowers et al., 1999; Oshima et al., 1997; Raju et al., 1995), these studies also have pointed out a need for better procedures for assessing the statistical significance of the DIF and DTF indices.

What is DIF?

Mellenbergh explained that Differential Item Functioning (DIF) occurs when an item on a test functions differently for different groups, given the ability level. Usually the groups are called reference group and focal group, and DIF means that the item has different characteristics for the different groups. Usually two types of DIF are distinguished: uniform DIF and non-uniform DIF (Mellenbergh, 1982). Hambleton arranged that Non-uniform DIF can be split into two types (crossing and non-crossing) and occurs when there is an interaction between group membership and ability level. In crossing non-uniform DIF, for one end of the ability level spectrum the item is easier for members of one group, whereas at the other end of the ability level the item is easier for members of the other group. In non-crossing non-uniform DIF, the item is of similar difficulty for both groups at one end of the ability spectrum, but different difficulties for the groups at the other end of the ability spectrum. Hambleton believed that in an IRT framework this means that the a-parameter and the b-parameter are different. Although in general uniform DIF is the most common type of DIF, previous applied research has found non-uniform DIF in operational tests as well (e.g. Hambleton and Rogers, 1989). Therefore just testing for uniform DIF is insufficient. Guler described that one issue in the detection of DIF is the presence of impact. When the focal group and reference group differ in their underlying ability distribution, i.e. when one group has a higher average ability than the other group, this is called impact. The presence of impact can make the detection of DIF more difficult (e.g. Guler and Pen_eld, 2009). Regardless of the type of DIF, the issue is that the item does not function the same for members of different groups, which can make a test unfair if the item is treated as functioning the same in both groups. Graphical Differential Item Functioning Several DIF approaches have straightforward graphical interpretations. Within the context of item response theory (IRT), DIF is conceptualized as differences between the item characteristic curves (ICCs) for two groups receiving the same item. It is not surprising that several IRT-based DIF approaches are graphical in nature. For instance, several authors have suggested DIF measures that are based on the area separating ICCs (e.g., Raju, 1988; Rudner, Getson, & Knight, 1980). Such measures can often be represented as shading on a plot of the two ICCs. Thissen and Wainer (1990) focused on the calculation of confidence bands around individual ICCs, but they described how these bands could be calculated separately for two subgroups and then visually compared as a DIF measure. The authors use a sampling approach based on multiple imputations to approximate the variability around an individual

ICC, and they derived relationships between the number of samples taken and the confidence associated with the resulting confidence bands. Pashley (1992) took an additional step and provided a method for calculating exact confidence bands around the difference function directly. The resulting func- tion could be examined to identify locations of local DIF, ranges for which the confidence bands do not include zero. Pashley's work builds upon the work of Hauck (1983) on methods for calculating confidence bands for logistic regression lines. Hauck provided closed-form expressions for the confidence bands using Scheffe's method and a form of the Cauchy-Schwartz inequality. Both the Rasch and two-parameter-logistic (2PL) IRT models are logistic response curves, so Hauck's approach can be applied directly in these cases.

DIF Procedure and Limitations

Incipient procedures for assessing DIF focused on dichotomous items (Camilli & Shepard, 1994; Holland & Wainer, 1993; Penfield & Camilli, 2007; Roussos & Stout, 2004). Tests of DIF in polytomous items address whether individuals having the same level of proficiency, but belonging to different groups, have the same chance of obtaining each score level of the polytomous response variable. A limitation of traditional measures of DIF for polytomous items is that they provide only an item-level index of the DIF effect (or an item-level test of the null hypothesis of no DIF) and thus provide no information concerning which score levels are implicated in the DIF effect or whether some score levels are implicated more than others. For this reason, traditional DIF measures for polytomous items can be conceptualized as omnibus measures of DIF. Because omnibus measures of DIF provide no information concerning which score levels are manifesting the DIF effect, they provide limited information to help guide the identification of specific components of the item manifesting the DIF effect and the potential causes of the DIF effect. The limitations of omnibus DIF measures make clear the need for a DIF methodology that examines measurement equivalence in relation to each score level of the polytomous item. The probability of observing each score level of a polytomous item is defined according to a series of step functions describing the chance that an individual will progress, or step, from one score level to a higher score level (e.g., the step from a score of 1 to a score exceeding 1, the step from a score of 2 to a score exceeding 2, etc.). It is the properties (i.e., underlying parameters) of these step functions that ultimately dictate the probability of observing each score level for an individual with a particular level of ability (Baker, 1992). As a result, an examination of the between-group difference in measurement properties in relation to each score level can be pursued through an examination of the between-group difference in the properties of the step functions underlying the polytomous item. This framework has been referred to as differential step functioning (DSF; Penfield, 2006, 2007). The framework of DSF provides a mechanism for examining the between-group difference in measurement properties at each step, thus providing detailed information concerning where along the polytomous response process a lack of measurement equivalence may exist for the groups under consideration. The framework of DSF provides DIF analysts with several advantages over the omnibus measures of DIF. First, tests of measurement invariance based on the DSF effects can be more powerful than the omnibus DIF tests when the magnitude and/or sign of the DSF effect varies across the steps of the underlying polytomous response variable (Penfield, 2006, 2007). In the extreme case where the sign of the DSF effect changes across the steps (i.e., is positive for one step but negative for another), the power of DSF-based tests of invariance has been shown to be more than 10 times that of the omnibus tests of DIF (i.e., a power of .045 for the omnibus test of DIF compared with a power of .85 for the test of DSF; Penfield, 2006). A second advantage of the DSF framework is that it allows the DIF analyst to pinpoint precisely which score levels (or steps) are responsible for an observed DIF effect. That is, if a polytomous item is flagged for DIF, then the analysis of DSF can be used to isolate the components of the item that require further content review and possible revision and ultimately suggest the factors causing the DIF. Because the identification of the causes of DIF is the key to decisions about item revision and/or removal (Bolt, 2000; Douglas, Roussos, & Stout, 1996; Gierl & Khaliq, 2001; Oshima, Raju, Flowers, & Slinde, 1998; Scheuneman, 1987; Schmitt, Holland, & Dorans, 1993; Swanson, Clauser, Case, Nungester, & Featherman, 2002), the framework of DSF can play a pivotal role in such decisions. In addition, the growing interest in the consideration of cognitive strategies used in responding to items (DiBello, Roussos, & Stout, 2007; Leighton & Gierl, 2007; Mislevy, 2006) places a new emphasis on understanding between-group differences in measurement properties in relation to these strategies. DSF provides a mechanism for identifying between-group differences in strategies underlying the responses to polytomous items. To date, the only accounts of DSF and related methodology have been technical and have provided limited guidance on the use and interpretation of DSF results. In this article, we present a nontechnical overview of the DSF framework and available methodology for assessing DSF and provide recommendations for the use and interpretation of DSF analyses. Issues of particular importance include: (a) how the results of a DSF analysis can help target investigations into the causes of DIF, (b) what methods can be used to evaluate DSF, (c) what criteria should be used to flag large DSF magnitudes, and (d) how DSF analyses can be most effectively used in conjunction with traditional DIF analyses. In addition, we illustrate the use of DSF using a real data set.

Differential Item Functioning (DIF) Analysis

For a test item to display DIF implies a persistent interaction between the performance of a subgroup of test takers and an attribute (e.g., age, gender, race, or nationality), which would give an unfair advantage to that subgroup over another (see Kunnan, 1990; Zeidner, 1986, 1987). To meaningfully impact test scores, this interaction must be not only too improbable to be attributable to chance but substantive as well. Statistically significant DIF indices may nevertheless be too small in magnitude to have any meaningful effect on the measurement (Linacre, 2010 a). Therefore, to cause test bias, DIF must be statistically significant (p < .05), substantively impact observed test or test item performance, and have a theoretically sound cause. Significant and substantive DIF indices imply that test scores no longer represent only the intended latent variable; they also represent an unintended and unmodeled secondary dimension (Wright & Stone, 1988). Unmodeled secondary dimensions may be either simple or complex (Jang & Roussos, 2009). The presence of a simple secondary dimension indicates that most test items measure the intended trait but that a group of items measures a secondary attribute that is nevertheless targeted on the intended trait. These items form an “auxiliary dimension” (Jang & Roussos, 2009, p. 242). The presence of a complex secondary dimension means that test items measure unintended traits, whose degree and type differs from item to item (Jang & Roussos, 2007, 2009). In tests with complex secondary dimensions, test items have primary and auxiliary dimensions, which measure the latent trait, and at least one “nuisance dimension,” which does not (Jang & Roussos, 2009, p. 242). Ackerman, Gierl, and Walker (2003) referred to DIF caused by auxiliary dimensions as *benign* and that caused by nuisance dimensions as *adverse*. This study adopts Rasch-based DIF analysis; one of the most frequently used methods of DIF analysis. Wyse and Mapuranga (2009) argued that the Rasch method is broadly comparable to other methods and Cauffman (2006) and Edelen, McCaffrey, Marshal, and Jaycox (2009) have reported on the potential of the method to detect gender-based DIF in educational assessment. Ferne argued that Rasch-based DIF analysis has two preconditions: (a) unidimensionality, which holds when overall test scores are not contaminated by any irrelevant factor, and (b) local independence, which holds when test takers’ performance on a given test item is not influenced by their performance on another item (Ferne & Rupp, 2007). Dimensionality analysis and DIF analysis are conceptually distinct. Dimensionality analysis yields information about secondary dimensions that are relevant to *all* test takers, whereas DIF analysis identifies conditional differences in response probabilities using defined variables (such as gender) that dimensionality analysis does not examine. Roussos and Stout (1996, 2004) argued that although the presence of DIF points to multidimensionality, “the presence of a secondary dimension does *not* automatically imply the presence of DIF. Some secondary dimensions cause DIF and some do not, depending on how the reference and focal groups differ in their proficiency on the secondary dimension” (Roussos & Stout, 2004, p. 108). Because of these distinctions, dimensionality analysis is an important precondition to Rasch-based DIF analysis (Ferne & Rupp, 2007, p. 129). Unfortunately, only eight of 27 studies in Ferne and Rupp’s survey of DIF analysis in language assessment provided evidence of unidimensionality. As previously discussed, DIF can be classified as either UDIF or NUDIF (Ferne & Rupp, 2007). UDIF indicates that the subgroup differences in the secondary dimension are constant across the main dimension and that “there is no interaction between ability level and group membership” (Prieto Maranon, Barbero Garcia, & San Luis Costas, 1997, p. 559). This implies that the item characteristic curves (ICCs) of two subgroups have identical slopes but different intercepts, indicating a consistent difference across the two subgroups (e.g., male and female), irrespective of the subclass being examined (e.g., low- or high-ability test takers). NUDIF, conversely, does vary with the ability level of test takers. In other words, the difference in performance between two subgroups is not consistent between subclasses of those subgroups.

DIF on the CLBA

Once a differential item functioning (DIF) item has been identified, little is known about the examinees for whom the item functions differentially. This is because DIF focuses on manifest group characteristics that are associated with it, but do not explain why examinees respond differentially to items. Ethnic, cultural, disability, and/or linguistic groups, little progress has been made in explaining why differential item functioning (DIF) occurs in many statistically flagged items. Because researchers’ attempts to understand the “underlying causes of DIF using substantive analyses of statistically identified items have, with few exceptions, met with overwhelming failure” (Roussos and Stout, 1996, p. 360), Roussos and Stout (1996) proposed a confirmatory approach to DIF.

A Confirmatory Approach to DIF

The Douglas, Roussos, and Stout (1996) confirmatory approach to DIF is a two-stage approach designed to link substantive and statistical methods in a DIF analysis framework. In the first stage of this framework, DIF hypotheses are generated from theory and substantive item analyses are conducted to classify the items according to an *organizing principle* or theoretical framework. A DIF hypothesis specifies whether an item or bundle of items designed to measure the *primary* or intended dimension also measures a *secondary* dimension or unexpected dimension that is suspected of producing DIF/DBF. The second stage in the DIF analysis framework involves statistically testing the hypotheses generated in stage one of the analyses. The statistical procedure and commercial software package selected for testing the hypotheses in the current study is the Simultaneous Item Bias Test (Stout and Roussos, 1999).

Differential Item Functioning (DIF) and Bias

In order to investigate the research questions, the current study drew on differential item functioning (DIF), a common approach used in the language testing literature to investigate bias. Differential item functioning is generally defined as existing when two groups of test-takers, who are otherwise matched in ability on a construct, have different probabilities of answering an item correctly (see Ferne & Rupp, 2007). A DIF finding, which in essence signifies the advantage of one group over another, may be attributed to the influence of construct-irrelevant variance on the studied item (and so indicate 'item bias'). On the other hand, two groups may differ in a construct-relevant way, in which case DIF may indicate impact rather than bias. DIF is therefore regarded as 'a necessary but not sufficient condition' for establishing an argument for bias (McNamara & Roever, p. 83). Various procedures have been used to calculate DIF, and according to McNamara and Roever (2006) these can be classified into four categories: analyses based on item difficulty, nonparametric approaches, item response theory (IRT) approaches, and 'other' approaches (such as logistic regression). These approaches have emerged more or less chronologically, with item difficulty approaches often found in early DIF studies, and IRT and logistic regression appearing more recently. Each 'family' of approaches has different strengths and assumptions. Ferne and Rupp (2007) suggest that a variety of methods is necessary as some studies have shown that certain methods may produce conflicting results for the same items (see, e.g., Kristjansson, Aylesworth & McDowell, 2005). Thus, multiple methods for DIF detection were selected for this study. Due to limitations in the sample size 2- or 3-parameter IRT approaches were not suitable (see McNamara & Roever, 2006). The two DIF detection procedures chosen as methods for the current study were the standardization procedure (also known as conditional p value) (Dorans & Kulick, 1983) and the Mantel-Haenszel procedure (Dorans, 1989; Mantel & Haenszel, 1959). Both procedures involve a comparison between a 'reference group' and a 'focal group'. The focal group is considered the 'group of interest', and the reference group is the group with whom performance is being compared (Holland & Wainer, 1993, p. xv). The standardization and Mantel-Haenszel procedures also involve matching test-takers on ability level; and each allows for matching to be performed using an external criterion. The selection of these two procedures reflects the approach taken by Roever (2007) in which both methods used together were found to be complementary, and useful for investigations with relatively small sample sizes (e.g. 250). Similarly, Hambleton (2006, p. 186) recommends these two procedures for identifying DIF with limited numbers of test-takers.

Using the Pattern of DSF Effects to Help Identify the Cause of DIF

As described in the previous sections, the presence of a DSF effect in a particular step can help the DIF analyst in targeting the specific score levels manifesting a potentially biasing factor. We can, however, make even more use of the DSF effects in understanding the causes of DIF through an analysis of the pattern of the DSF effects across the J steps of the polytomous item. In particular, the specific pattern of the DSF effects across the J steps of the polytomous item can help guide the analyst in identifying the possible cause(s) of the DIF effect and in making a decision about item revision or removal. Although there are an infinite number of patterns that the J DSF effects can assume, several general groupings of patterns are particularly revealing of the causes of the DIF effect. Penfield, Alvarez, and Lee (2009) described these groupings within a two-dimensional taxonomy of DSF patterns. The first of these dimensions distinguishes between pervasive and nonpervasive DSF. Pervasive DSF is observed when all J steps display a substantial DSF effect, and thus the DSF effect is *pervasive* across all score levels. The presence of pervasive DSF suggests to the analyst that the cause of DIF is exerting its influence at the item level. For example, pervasive DSF may be observed in a writing task where students are asked to respond to a particular prompt. In such an item, the presence of pervasive DSF would imply that the factor responsible for the lack of invariance is inherent in the content of the prompt itself. In contrast, nonpervasive DSF exists when only one or a few steps display a substantial DSF effect. The presence of nonpervasive DSF implies that the factor causing DIF may be isolated to one or a few steps. For example, consider a writing task in which DSF appears only in a score level that requires well-structured paragraphs, in addition to the characteristics required by the scoring criteria for the lower score levels. In this case, the nonpervasive DSF provides evidence that the DIF effect is not necessarily due to content in the writing prompt but rather is isolated to properties of the particular level pertaining to paragraph structure. Making this distinction between pervasive and nonpervasive DSF can prove valuable in determining whether the cause of DIF is due to an item level property or a property of one or more particular score levels. The second dimension of the DSF taxonomy pertains to the consistency of the DSF effects across impacted steps, distinguishing between constant, convergent, and divergent forms of DSF. Constant DSF is observed when the steps displaying a DSF effect are relatively equal in magnitude and sign. Although constant pervasive DSF provides evidence that the factor responsible for the DSF effect is a property of the item, constant nonpervasive DSF indicates the factor responsible for the DSF is restricted to the affected score levels and thus is not necessarily an item-level property. Convergent DSF describes the situation in which affected steps display a DSF effect of the same sign (i.e., favoring the same group) but different magnitude, providing evidence that the causal factors are manifested differentially across steps. It may be the case that an item-level effect impacts score levels differently, or more than one biasing factor is present. Divergent DSF is characterized by affected steps displaying opposite signs, meaning that the relative advantage shifts between groups across the steps. The presence of divergent DSF implies that the causes of the DSF effects are different for the affected score levels, and thus more than one causal property is at play. Identifying the presence of divergent DSF is of paramount importance because many DIF statistics are expected to be relatively insensitive when divergent DSF effects cancel one another at the item level, yielding a net DIF effect near zero.

Conclusion

Since the 1980s, the popularity of mixed effects or multilevel models has increased exponentially in several research domains, for example, in education, psychology, and biomedical sciences. Also in IRT applications, mixed (see, e.g., Adams, Wilson, & Wu, 1997; De Boeck & Wilson, 2004; Kamata, 2001; Mellenbergh, 1994). Furthermore, item response models can include random item effects (crossed with the random person effects), as discussed by Van den Noortgate et al. (2003). These important evolutions in item response modeling suggest new models and approaches for DIF. Traditionally, an item is said to show DIF if conditionally on the ability, the probability of correctly answering the item depends on the group the person belongs to and models and techniques for DIF treat both the items and the groups as fixed. Although in traditional DIF analyses DIF is considered specific and limited, this is not true if items or groups are considered random, a possibility that is explicitly mentioned in the taxonomy. For example, the effect of fixed groups may be modeled as varying at random over items, following a normal distribution.

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