Best practices in reporting analyses of questionnaires as objective rating scales of variable measures

What are the general objectives of this article?

1. To clarify the meaning and implications of objective measurement applied in questionnaire analysis
2. To outline some recurrent problems that must be reported when constructing measures using questionnaires
3. To understand the importance of Wright maps in rating scale analysis
4. To encourage questionnaire analysts to be more explicit about techniques used in addressing data problems

Abstract

Background: Questionnaires are frequently used as rating scales of latent variables such as knowledge, anxiety and treatment outcomes. However, reporting the steps involved before generating the final 'measures' often fails to present known limitations and robust solutions to the problems common in questionnaire data.

Aim: To highlight some common problems in questionnaire data and suggest techniques of constructing objective measures during rating scale analysis.

Discussion: Majority of questionnaire users generate variable measures, either for educational or clinical research purposes, without providing adequate explanations of the steps taken to address inherent

limitations that may worsen the error terms in the outcome measure. On the background that the usefulness of any measure depends on the least allowable error implies that best practice approach must be adopted during rating scale analysis. The best practice model therefore states that the most current scientific information in a discipline be engaged in addressing pertinent data problems. Hence this paper proposes practical solutions to some shortcomings in reporting questionnaire analysis, based on modern theories of objective measurement in advanced statistics.

Conclusion: Cursory attention is given to the problems in questionnaire analysis as most users do not convincingly justify the applied measurement techniques before presenting variable estimation. Reporting the techniques used to address data complexity by engaging objective measurement parameters ensures best practice and emphasises the credibility of the outcome measure.

Implications: For a variable measure to be immediately useful, having limited error terms comparable to rating scales such as a clinical thermometer or height measure from a measuring tape, known limitations predisposing to increasing error must be identified and objectively resolved.

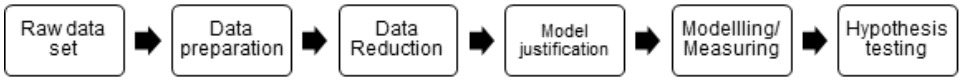
Introduction: Traditional methods of analysing questionnaires as rating scales in health and educational research “look good from afar” but far from being good because rigorous treatment of questionnaire data proposed in advanced statistics is not always inculcated during the

analysis (Thompson, et al., 2005; Colgrave, et al., 2020). In spite of the popularity of questionnaires as valid rating scales of research variables, commensurate commitment to exemplary analysis is at best rudimentary as applied measurement models are not adequately discussed nor justified (Bond & Fox, 2007). The primary objective of rating scale analysis is, foremost, to generate credible variable measure with minimal error terms. Achieving this purpose is however often confronted with common shortcomings found in questionnaire data and conventional analysis. Acknowledging that many misleading outcome measures from controversial computational methods are common, Leung et al. (2012) suggested that there should be an appraisal framework for assessing quality of a rating scale and the outcome measure. Yet, Leung et al. (2012) failed in their suggestions to incoporate the principles of objective measurement that may improve the rating scales or any measures produced using questionnaires. Consequently, Boone (2014) stated that routine publications about questionnaire analyses are neither consistent in reporting the key limitations nor provide adequate explanations on techniques used to minimise the error terms in the analysis. Bond & Fox (2007), extending the objective measurement models proposed by Wright & Masters (1982) into the human sciences, argued that some quantitative researchers add up concrete scores from respondents and follow up conducting parametric statistics as if questionnaire data are linear interval scales. Linacre (2021) noted that the problems found in analysing questionnaire data are not really new, but the lack of

computer software and required skills are the major barriers to engaging the modern theory. This argument however seems to have gained increasing attention as more user-friendly computer software are now available for conducting objective measurement from questionnaire data including Winsteps, RUMM2030+, ConQuest 5, Facets, WINMIRA and R (Rasch measurement analysis software directory, 2022). Simultaneously, the Institute for Objective Measurement (IOM) has stepped up formal online workshops or seminars, providing technical assistance and free access to software such as Bigsteps, Mplus, Minifac, Ministep and Openstat. Notwithstanding the advances in applied measurement research, questionnaire users in health-based disciplines are yet to adopt the most current techniques of variable measurement as the gold standard of rating scale analysis. Health care researchers (Sackett, et al., 1996; Melnyk, 2017) are unequivocal in linking improved quality patient care with evidence-based practice: a model of treatment that advocates for objective research evidence in making clinical decisions. The implication here is that, for questionnaire analysis to represent efficient and effective outcomes conceptualised within evidence-based practice, exemplary statistical techniques must be engaged. On this background, this paper aims at two important objectives: (a) To explain the concept of objective measurement using questionnaires; (b) To argue that a rating scale analysis ought to follow and clearly report scientifically sound techniques rooted in objective measurement theory. Consequently, for clarity purposes, the use of clinical thermometer

(routinely used measuring tool by nurses) is repeatedly introduced in this discussion to illustrate the meaning and application of objective measurement. The aim is that presenting a comprehensive implication of measurement using clinically relevant measuring tool may motivate nurse-researchers (and other questionnaire users) to think deeper about rigorous techniques in analysing questionnaires as rating scale. The diagram below is an idea of step-by-step approach to using questionnaire as a rating scale presented in the ensuing article.

Figure 1: The data analysis process



Understanding applied objective measurement

A good understanding of the meaning and practical applications of parameters of objective measurements is essential for generating objective measures from questionnaires, similar to using a clinical thermometer. According to Wright & Masters (1982), objective measurement using questionnaire or any other measuring tool is underpinned by four principles: 1. The deliberate perception of a variable as a single entity or dimension (Unidimensionality); 2. The belief in the existence of a linear magnitude or possibility of modelling a variable into a linear scale (Linearity); 3. The belief that the process of measurement is so consistent that the same outcome (variable measure) will be reproduced without further modifications to the techniques or scale notwithstanding the subjects measured (Non-

sample dependent measures); 4. The desire to engage in statistical comparisons of respondents and the variable in terms of higher or lesser using numbers. The first principle (unidimensionality) must be accounted for at the initial phase of developing the questionnaire (Wright & Stone, 1979; Omolade, et al., 2022), hence not discussed here. Principles 2&3 (linearity and non-sample dependent measurement) are the focus of this article contextualised within analysing questionnaires as rating scales. Principle 4 is about performing descriptive and inferential statistics on the measure generated after applying principles 2 & 3.

The four principles above mirror the core philosophy of scientific measurement applied in designing routinely used clinical tools such as clinical thermometer or measuring tape for grading patients' heights. The implication is that if measures generated from questionnaires must gain comparable mathematical merits accorded temperature measure, analysts must report the techniques engaged to adhere to all the four parameters of objective measurement during the analysis. In other words, the ritual of merely counting numbers (from respondents) as variable measure must be replaced with robust mathematical techniques rooted in objective assessment.

Measurement of a latent variable using questionnaires combines both relevant theories and applied mathematics (Wright & Masters, 1982; Boone, et al., 2014). Bond & Fox (2007) stated that while the theoretical inputs from literature evidence has grown, the background mathematics is stagnated by widespread simplistic approach to

measure construction. For instance, to measure nurses' evidence-based practice competence or ability, a number of items or indicators fitting into the recognised definition of evidence-based practice skills will be collated together. The usual practice in questionnaire design is to present the indicators as questions or statement of fact for respondents to endorse or disagree with. Yet, Psychometricians recognise that, even at this preliminary stage of measuring, there can be misinterpretations of the indicators by respondents thus the need for evaluating the psychometric properties of the questionnaire (Linacre, 2004; Sakib, et al., 2020). Despite the excellent psychometric properties of a rating scale, estimating the outcome measure is still prone to remarkable computational errors except the best techniques are engaged (Leung, et al., 2014). According to Hilaliyah et al. (2019), error-prone measurement results by applying observed score (X) as variable measure without applying any techniques that minimise measurement (E) error from true score (T). To the opposite, engaging objective measurement techniques mean modelling questionnaire data to generate a measure with the least possible measurement error. Correspondingly, a visual display of linear continuum (principle2) of the rating scale derived from the conjoint relationship among the indicators on a questionnaire cannot just be assumed. More importantly, only at this point are the measures generated considered independent of the measured sample (principle3) hence proving the consistency in the rating scale. Linearity is so important, for instance using a thermometer, because only by upholding a linear relationship

of indicators can one degree centigrade be universally agreed as the true difference between 35 degrees centigrade and 36 degrees centigrade when measuring patients' body temperature. In contrast, a respondent whose observed score is 20 on an evidence-based competency questionnaire cannot be described as twice more competent than another respondent who scored 10. Similarly, the scores 20 or 10 standing alone do not explain what competency the respondents possess based on the questionnaire initially administered.

The steps outlined below will highlight the techniques that improve rating scale analysis in generating objective variable measure.

Data Preparation

Data collected using questionnaires is analysed by converting a pool of categorical and numerical figures into a simpler meaningful whole while adhering to the basic principles of applied mathematics. In a broad sense, data analysis bifurcates into data reduction and measurement modelling guided by objective computation principles and mathematical theories (Wright & Masters, 1982). Applying useful models to manage the analysis ensures the whole procedure is scientifically robust and systematically objective. Yet measurement models, like any other useful concepts, cannot be applied capriciously but consequent upon screening the data for problems the applied model is meant to solve. Therefore, data examination is the first stage of analysing a quantitative data set. Data examination or inspection or data scrutiny or data preparation can be used conterminously to mean the initial screening of a data set for potential strength and limitations.

It is valuable to recollect that the observed numbers (data), from questionnaire administration, are products of unobservable interactions or reactions between the rating scale and the research variable (Wright & Masters, 1982). Clinicians will agree that thermometer reading is an outcome of liquid mercury in the evenly graduated glass tube reacting to a patient's body temperature. Underpinned by the same principle, a case can be made for questionnaires as measuring tools such that the numbers endorsed by respondents be treated as outcomes of reactions between the questionnaire items and the research variables investigated during data collection stage of a study. However, many problems can emerge at this stage demanding thorough investigation before committing to any meaningful calculations. For example, one may argue that some self-reported answers to the questionnaires do not represent the predicted reactions between the questionnaire and the research variable because the items on the questionnaire ought to be linearly related as in the case of graduated markings on the clinical thermometer. Thus, a fundamental question may be *Can there be responses in a questionnaire that do not match the predetermined measurement criteria?* This problem has been known by many researchers for long yet glossed over or rationalised until the invention of Rasch techniques (Boone, 2016). Therefore, the critical function of a good measurement process is, first, to examine the raw data for misfitting responses or related problems and report treatments applied (Boone, et al., 2014). Misfitting persons or responses do not abide by the objective measurement model, implying responses from such

persons are inconsistent with the parameters of computing objective variables measures. Hence, the quality of data collected must be screened or inspected for anomalies that may limit the overall performance of the data. Some of the common problems and solutions are explained as follows.

Coding errors: Codes or points are allocated to the ordinal categories of a questionnaire on the basis that the highest point shows the highest amount and the lowest point for the least measure. In a negatively phrased questionnaire, coding is reversed. For example, 1, 2, 3 & 4 may correspond with Strongly disagree, Disagree, Agree and Strongly agree on positively phrased items. In negative indicators, the points must be reversed such that 4 is allocated to Strongly disagree and 1 to Strongly agree. In most cases coding is done when designing a questionnaire. But if required, recoding after data collection to correct any unintended mistake is possible when the indicators are screened or inspected.

Completeness: The completeness of the data collected highlights two issues. Foremost, all the respondents may not use all the items provided on the questionnaire, hence the problem of missing data emerges. Secondly, the number of respondents may not match the sample size earlier calculated (sample size inadequacy) even though a provision was made for 20% attrition. Both routine and objective measurement analyses recognise these problems, but some researchers often fail to provide good argument on final decisions made. Addressing missing data in the traditional method or the classical test theory (CTT) is inconsistent being not supported by any measurement theory (Bond &

Fox, 2007). However, unlike CTT, the problem of missing data is well accounted for in the Rasch measurement technique because the probability theory is used to assess observed questionnaire data against expected measurement model.

The lack of linearity among the indicators: Indicators' conjoint order and linearity are fundamental requirements before adding scores together (Wright & Masters, 1982). Until items are linked together based on the level of difficulty, calculations cannot begin because ordinal categories lack additivity and should not be mistaken as valid measures of a research variable (Boone, 2016). Measures of a research variable become an arbitrary label if the items used in the measurement do not show meaningful relationships with other items on the same scale in such a way that one can decipher more or less of the research variable by marking the items or indicators (Wright & Masters, 1982)

"Perfect score" problems: Perfect scores apply to respondents who choose the lowest or highest options for all the indicators notwithstanding the coding system. The primary aim of administering a survey is to discriminate among respondents, but perfect scores do not align with this measurement requirement for a questionnaire to be treated as a valid rating scale. Wright & Masters (1982) explained that perfect scores indicate a mismatch between the survey items and the respondents. In other words, for the lowest perfect score, the survey or test may be too difficult and above the respondent's interest or ability. For the highest obtainable perfect score, the survey seems to be too easy, and the respondents' ability is above the difficulty presented by

the indicators. Using the illustration of clinical thermometer again to illustrate a perfect score, the thermometer is calibrated within the range of human body temperature so that both lower and upper limits must never be reached. If a thermometer reads the lowest possible temperature gauge for any individual, then that reading requires further investigation and cannot be used as the basis for clinical intervention. The same problem applies if a thermometer records the highest possible temperature repeated times on a patient. Interestingly, Rasch measurement technique is designed to screen a data set for "perfect scores" and exclude such scores from the analysis.

Model fit: Model fit suggests comparing observed data with the Rasch objective measurement model to assess fitting of items and respondents to the model. Boone et al. (2014) called model fit diagnosis “data quality-control steps” to determine consistency in the observed scores. During questionnaire development, fit assessment focuses on the items or indicators while before outcome measure construction, respondents’ fitting is evaluated to diagnose individuals with complicated pattern of responses. Boone (2016) argued that model fit can identify increased measurement error from respondents overtly guessing answers, distracted when using the scale and any other pattern disconnected from predetermined measurement parameter. The implication is that respondents who clearly violated the fitting diagnostic criteria should be excluded from constructing the final measure of the research variable. Rasch theory of obective measurement uses the terms “Information-weighted fit and Outlier-sensitive fit (Infit & Outfit)

Mean Square Values" to describe the statistical techniques for evaluating model fit (Bond & Fox, 2007). The most frequently applied index of misfit as a rule of thumb is Outfit Mean Square Value above 1.3 (Boone, 2016).

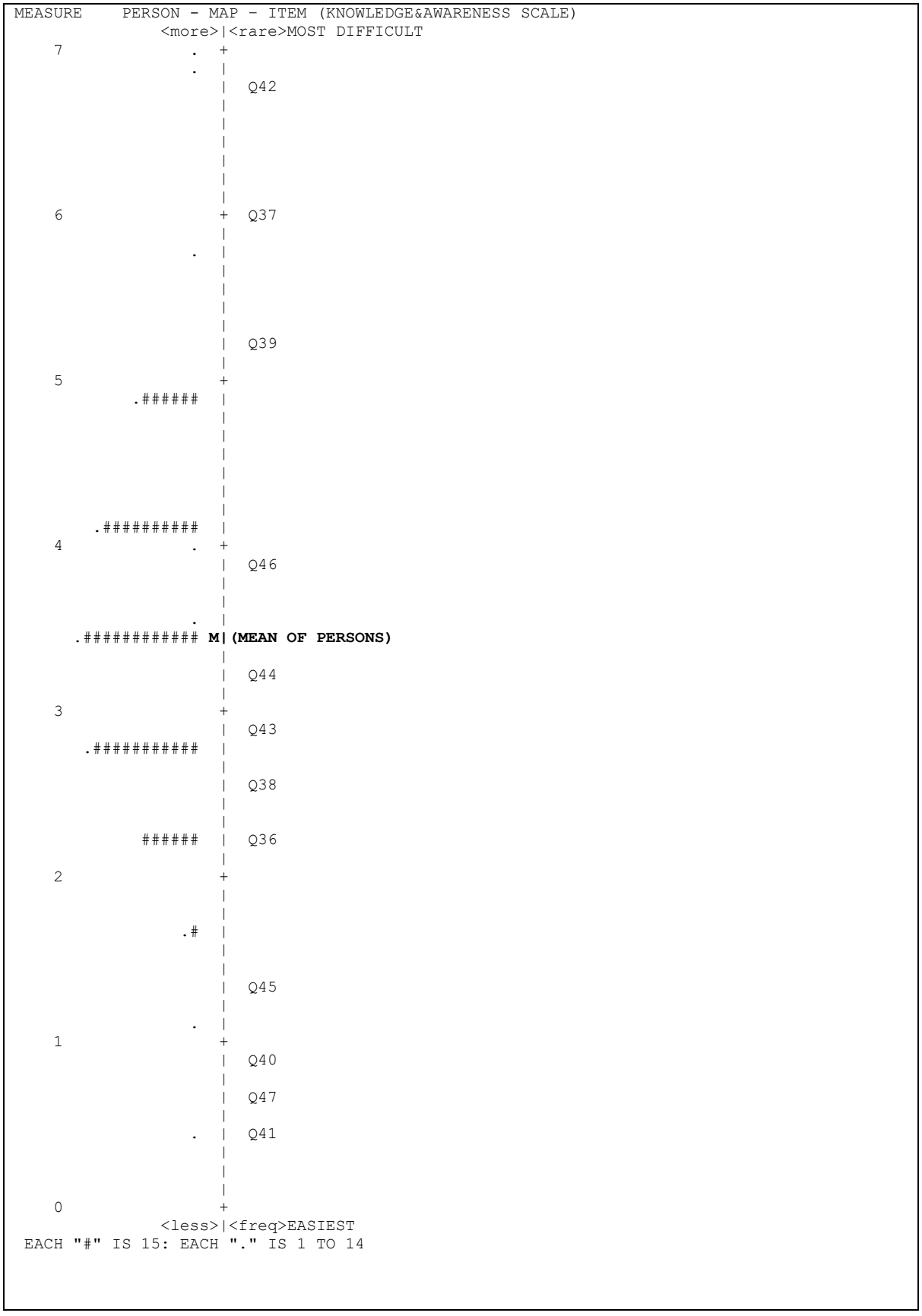
Measure construction (Wright map): Having identified some key problems that questionnaire data may present, any applied measurement model ought to provide mathematically sound solutions to the problem. In Rasch techniques, generating a variable measure is presented as a linear logit scale on a Wright map (named after a mathematician, Benjamin Wright). The Rasch measurement models, which historically began with analysing dichotomous scales, have advanced into analysing polytomous Likert-type scales and partial credit model of measurement (PCM). As the name suggests, "partial credit" is a measurement model that proposes partial score should be awarded to category options based on the degree of deviations among the category point in such a way category points present as an order of partial score of adjacent categories (Bond & Fox, 2007). Including the benefits that Rasch model produces interval score replica of the true score and outcome measure is informed by probability, Wright map construction is the most unique feature of Rasch analysis (Boone, 2016).

Beyond generating variable measures, Boone (2016) emphasised the importance of the visual representation of items, persons and measures on the Wright map so that respondents' measures can be expressed in terms of skills or knowledge the respondents have mastered or not. For

instance, presenting average score (50% or 70%) of the evidence-based competency scale or any cognitive assessment is not enough, a relevant question is what is the implication of the score on skills mastered? Correspondingly, Wright map combines respondents, measures and items in the map. Either for clinical reasons or educational purposes, having a visual qualitative interpretation of measures linked to the questionnaire items helps to easily spot critical success factors in a population. The implication is that corresponding intervention can accurately target specific gaps in competency. Furthermore, Wright map analysis is powerful enough to describe levels of significance when group means are compared using ANOVA or t-test. If there is a finding suggesting a significant difference is found among groups, Wright map can isolate the indicators marking differences. Hilaliyah et al. (2019) summarised the advantages of a Wright map into three: 1. Displays connections among measure, persons and indicators; 2. Indicators define respondent in a non-sample dependent version; 3. Respondents' measure can be linked with demographics (age, years of practice, place of work) of interest. To further appreciate Rasch technique of measure construction, see the Wright map below. Figure 1 is a Wright map of an unspecified variable depicting the linear relationship among persons and items based on the order of ability and difficulty respectively. The 14 items (Q36 to Q47) outlined on the right side are ordered from the easiest (Q41-bottom) to the hardest (Q42-top). This plot was derived from the output file on Winsteps following the Rasch measurement modelling. The middle line is the "logit or

Rasch" scale modified to present the measures from 0 to 7 logit eliminating the infinite negativity and positivity measure. On the left side, each "#" represents 15 respondents and each "." depicts 1 to 14 respondents. The mean measure for this group is 3.5 logit and more than 420 respondents scored at least above the mean score for the group. If this Wright map presumably describes the evidence-based practice competency of a group of clinicians, respondents located closer to the top of the linear continnum are more competent than those closer to the bottom of the scale. In addition, any respondent scoring at least 3.5 (mean score) will find tasks Q44, Q43, Q38, Q36 and Q45 easier to perform than those below point marked "M" on the scale. Also, the result shows it requires more than average competency level to succeed in tasks Q46, Q39 while tasks Q37 & Q42 will require even higher competency measure. Through further examination of the respondents' measure, researchers can also find out if respondents expected to have low measures have lower measures than respondents predicted to have higher competency. Since the Wright map presents the questionnaire items ordered according level of difficulty, Boone (2016) illustrated how the map can be used to produce a high-quality questionnaire for objective measurement. Further clarification on Rasch measurement models can be found in books such as Wright & Master (1982); Bond & Fox (2007) and Boone et al. (2014).

Figure2 : Example of a Wright map of an unspecified variable



Deciding appropriate statistical software: Data analysis engages human inputs and statistical software to generate output files (results).

While good software exists for processing various numerical data sets, it is obligatory for an analyst to inspect, specify and input commands into the computer. Computer software does not have the inbuilt capacity to identify sources of numerical figures, neither can the software apply the appropriate statistical methods except by analyst's input. Using questionnaires is not as simple as it is being purportedly reported because the analysis process is confronted with the complex problems demanding excellent knowledge in applied mathematics and computer to resolve. Only Rasch software is able to construct measure computations of measures. Factors that may influence choice of Rasch software to use include accessibility, affordability or subscriptions, avaialbility of manual, personal skills or past experience. Linacre's (2021) manual on conducting rating scale analysis on Winsteps is a easy-to-follow guide for questionnaire users and requires subscriptions. Table 1 below summarises the problems explained above and suggested solutions.

Table 1: Summary of questionnaire data problems and solutions

Data analysis problems and treatment technique
Coding errors: Inspect and recode data as appropriate
Completeness: Inspect data and check for attrition

Perfect scores: Apply the Rasch measurement model
Model fit: Apply the Rasch measurement model
Linearity: Apply the Rasch measurement model
Computing respondents' measures: Wright map analysis
Deciding the best statistical methods: Follow good statistical guidelines
Choosing appropriate computer software: Winsteps and SPSS

Implication and conclusion: Reporting the problems and techniques applied to resolve measure construction represent best practices in rating scale analysis. This implies analysing questionnaires as objective rating scales of research variables ought to adhere with the four parameters of objective measurement including evidence of unidimensionality, linearity, consistency and additivity of the indicators on the questionnaire. Unfortunately, in many nursing journals, the use of questionnaires as a rating scale of research variable lags best technique proposed under theory of objective measurement. In this paper, objective measurement is conceptualised under the Rasch technique with special attention drawn to the use of Wright map. The argument is that questionnaire measures ought to pattern objective technique otherwise measurement error will derail the process into

unintended misleading conclusions. Overall, this paper proposes to questionnaire users in nursing and related fields to embrace the rigours and benefits offered in applied objective measurement theory when reporting questionnaire analysis.

Limitations: Even though the aim of this paper is to ensure rating scale analysis is objectively conducted with least possible error, objective measurement using questionnaires ought to begin with the design of the measuring tool. Therefore, we suggest to questionnaire developers to study monographs, worked examples and relevant textbooks on developing high quality questionnaires in human sciences by authors such as Bond & Fox (2007); Boone (2016); Sakib et al. (2020) and Omolade et al. (2022).

Key points:

1. Best practices in advanced measurement technique are not routinely applied by researchers.
2. There are four key principles of objective measurement that must be inculcated in rating scale analysis.
3. Engaging Rasch objective measurement techniques ensure variable measures are true scores rather than observed scores.

References

Bond, T., & Fox, C. (2007). *Applying the Rasch Model: Fundamental meausrement in the human sciences* . mawah: NJ:Lawrence Erblaum & Associates.

Boone, W. J. (2016). Rasch analysis for instrument development: Why, When, and How? *Research Methods*. doi:10.1187/cbe.16-04-0148

Boone, W., Staver, J., & Yale, M. (2014). *Rasch analysis in the human sciences.* Dordrecht: The Netherlands: Springer.

Colgrave, J., Stasa, H., & Fraser, J. (2020). Validity and reliability of the psychometric properties of achild abuse questionnaire. *Nurse Researcher*. doi:10.7748/nr.2020.e1677

Hilaliyah, H., Agustin, Y., Setiawati, Hapsari, S. N., Rangka, I. B., & Ratodi, M. (2019). Wright-map to investigate the actual abilities on math test of elementary students. *ournal of Physiscs*. doi:10.1088/1742-6596/1318/1/012067

Leung, K., Tarvena, L., & Waters, D. (2014). Systematic review of instruments for measuring nurses' knowledge, skills and attitudes for evidence-based practice. *Journal of Nursing*, 2181-2195.

Leung, K., Travena, L., & Waters, D. (2012). Development of an appraisal tool to evaluate strenghth of an instrument or outcome measure. *Nurese Researcher, 20*, 13-19.

Linacre, J. (2004). Test validity and Rasch Measurement: Construct and content. *Rasch Measurement Transactions, 18*(1), 970-971.

Linacre, J. M. (2021). *A user's guide to WINSTEPS MINISTEP Rasch-Model Computer Programs Program Manual 4.80.0.* Chicago: IL:Winsteps.

Melnyk, B. M. (2017). Models to guide implementation and sustatinability of evidence-based practice: A call to action for furthe use and research. *Worldviews on Evidence-based Nursing, 14*(4), pp. 255-256.

Omolade, O. K., Stephenson, J., Padam, S., & Keely, A. (2022). Is this a good questionnaire? Dimensionality and category functioning of questionnaires used in nursing research. *Nurse Researcher*. doi:10.7748/nr.2022.e1842

Rasch measurement analysis software directory. (2022). Retrieved from Institute for Objective Measurement: www.rasch.org

Sackett, D., Rosenberg, W. M., Gray, J. A., Haynes, R. B., & Richardson, W. S. (1996). Evidence based medicine: what it is and what it isn't. *British Medical Journal, 312*, 71-72.

Sakib, N., Bhuiyan, A. K., Hossain, S., AlMamun, F., Hosen, I., Adullah, A. H., . . . Mamun, M. A. (2020). Psychometric validation of the Bangla fear of COVID-19 Scale: Confirmatory factor analysis and Rasch analysis. *International Journal of Mental Health and Addiction*. doi:10.1007/s11469-020-00289-x

Thompson, B., Diamond, K. E., Mcwilliam, R., Synder, P., & Synder, S. W. (2005). Evaluating the quality of evidence from correlational research for evidence-based practice. *Exceptional Children, 71*(2), 181-194.

Wright, B. D., & Masters, G. N. (1982). *Rating scale analysis.* Chicago: MESA Press.

Wright, B. D., & Stone, M. H. (1979). *Best Test Design.* Chicago: MESA Press.