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The interpretation of single individuals' measurements¹

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Abstract

This article concerns the interpretation and construction of measurements for single observational units, including the creation of scales or indexes to improve the quality of the measurements. The focus is on the individual as the observational unit in psychology, but to present a broader perspective related measurement issues in official statistics are also discussed. It is concluded that when individual measurements are to be interpreted, measurement precision must be given priority and taken into account in the research design. Unfortunately, most measures in psychology are not highly reliable, and examples are given demonstrating that such measures do not normally allow the researcher to make inferences about single individuals. Methods for testing questionnaires in a cognitive laboratory that have been developed within survey research can provide useful tools to increase both reliability and validity of single questions/items.

Keywords: Measurement, individual, treatment, psychometrics

Measurement issues are of crucial importance in almost any area of psychology and also in other disciplines where measurements are used. In this article, the construction and interpretation of single observational units' measurements are discussed. In psychology, this issue is especially important when the individual is the observational unit of interest, for instance when a person-oriented approach is applied (Bergman & Magnusson, 1997). However, also in areas far removed from psychology, the task of optimally measuring single observational units can be quite important, whether these units are individuals or something else (e.g., geographical regions or companies). There is a degree of universality of such measurement considerations that makes them relevant also for psychologists. Therefore, this article takes its starting point from outside psychology, namely from the creation and interpretation of single observational units' measurements in statistics, especially

official statistics. Against this background, the focus is then shifted to measurement issues in psychology that arise when a study involves the interpretation of single individuals' measurements.

In official statistics, the focus is often on the estimation of population parameters from data for a sample. For instance, the estimated percentages with "very good" self-reported health in different strata of the Swedish population are reported, based on the sampled individuals' answers to the single question "How do you rate your general health?" (a response scale 1 - 5 is then often used where "1" is labeled "very good"; this question appears in many sociological and epidemiological studies; see, for example, Socialstyrelsen, 2004). Much research has been done to develop sampling designs and estimation methods and also to handle the effects of measurement errors of different kinds. The interpretation of single units' measurements is then normally not of primary interest. Sometimes in official statistics also another type of information aggregation is done where indexes are formed of several single questions or items which, taken separately, are not of primary interest. For instance, an indicator of global subjective well-being (SWB) is formed by summing the answers to the five items included in the Diener scale (Diener, 1994) and a number of countries are compared with regard to their average level of SWB.

The presentation will be restricted to the case where the individual is the unit of analysis and the article is divided into two main sections: (1) interpreting measurements for single individuals and (2) using individual measurements based on single variable information as contrasted to using measurements based on pooled information from many single variables (scales, indices).

Interpreting measurements for single individuals

When data from statistical surveys are analyzed, the focus can sometimes be on measurements of one or a few individuals. For instance, coming back to the SWB example, one might want to do a detailed study of those reporting an exceptionally low level of global SWB and attempt to find associated individual factors (e.g., living conditions, life events, and so on). Or take an example from psychology: A clinical psychologist wants to make inferences about a patient's level of alcohol problems based on the answers to the AUDIT instrument (Saunders, Aasland, Babor, de la Funte, & Grant, 1993). In both these examples, it is intuitively obvious that the reliability of the measurements needs to be higher than if the same measurements were used together with many other measurements for producing group statistics (e.g., to compute means for the whole sample, which would have a standard error much smaller than the individual error).

The individual is usually the unit of analysis in psychology and measurements can be of many different types (e.g., test scores, psychophysical ratings, excretion of stress hormones, attitude ratings, and scores on personality tests). For the present purpose, only measurements obtained by self-reports will be considered, assumed to be approximately interval scaled. They can be either used directly in their "raw form" to form variables in the study or they can be used for constructing a scale or an index. Usually, several items are used to build a scale. However, almost always errors of measurement are present and to take them into consideration some model of the errors is necessary.

The classical test theoretical model (CTTM) is a basic measurement model that is often used in psychology. In this model it is assumed that the obtained score is the sum of a true score and a normally distributed random error with an expected value of zero (Lord & Novick, 1968; for an example of using CTTM for test construction, see Sundström, 2008). In CTTM, the reliability of a measure obtained for a sample is defined as the ratio between the true score variance and the observed variance, and methods exist for estimating the reliability (e.g., by computing a test-retest correlation). Of course, more sophisticated measurement models are increasingly used (e.g., item response theory models, see Baker & Kim, 2004) but CTTM will suffice for the purpose of discussing the interpretation of individual measurements.

In psychology, the focus is most often on summary statistics, like mean differences between groups, correlations between variables, linear models and so on, and sometimes on making inferences to a population (although most frequently the samples are not random and sampling design is not much considered). A focus on interpreting single individuals' measurements is perhaps most common in the context of diagnosis in clinical psychology and in educational/vocational selection and guidance. Obviously, it is then important to have a high degree of measurement precision (i.e., a high reliability) to be able to interpret an individual's measurement and make a decision about that individual. Assuming CTTM, a confidence interval containing the individual's true score can be constructed and, broadly speaking, the reliability has to be high for the measurement to be useful for that purpose (above 0.80). Precise measurements can be obtained for some measures (e.g., a comprehensive IQ test) but this is not the case for most measures used in psychology, for which the reliabilities often are in the range 0.70 - 0.80.

Within many fields of psychology, only moderately reliable measurements can be sufficient. This presumption may be justified if the scientific question can be answered by analyses producing group statistics or by a model of the data that holds for all individuals in the sample. Many statistical models (structural equation models, latent growth curve models, etc.) can also handle certain types of errors. However, when the focus is on interpreting single individuals' scores the situation is different, as was indicated above. The number of research fields in psychology where this individual focus is central is also increasing. In fact, at least three newer directions in psychology have evolved that emphasize the need for interpreting single individuals' scores, and consequently demand that the measurements are highly reliable. They concern (1) the study of the single individual using statistical methods, (2) the study of average versus individual causality, and (3) the person-oriented approach for studying individual development.

It is hazardous to make inferences about individual development from group statistics

The first direction presented here concerns the renewed interest in studying the single individual's development with statistical methods. It has led to an increased recognition that only under strong assumptions can inferences be made about individual development from standard group statistics, calculated for samples of individuals. The studied process must then be assumed to be ergodic (Molenaar, 2004). Molenaar instead proposed a bottom-up approach where first a separate model is built for each individual, using data from many time points, and then the individual models are generalized. Of course, it is not a new thought that the individual is "lost in the statistics", being forcefully pointed out many decades ago by, for instance, Cairns (1986), Carlson (1971), and Magnusson (1985). Consider now the simple example presented in Table 1 where longitudinal information is presented about teachers' ratings of aggression from age 10 and 13 for a sample of 916 children. These 7-graded ratings are highly reliable and range from "1", indicating very low aggression, to "7", indicating very high aggression. The data were taken from the longitudinal research program Individual Development and adaptation (IDA; Magnusson, 1988).

_	Aggression age 13							
Aggression	1	2	3	4	5	6	7	All
age 10								
1	32*	31*	14	20	8	2	0	107
2	18	30	28	48	11	6	3	144
3	20	29	37	57	19	15	1	178
4	12	37	54	105	52	30	10	300
5	3	5	11	38	19	17	9	102
6	2	4	10	10	10	12	11*	59
7	0	0	1	6	6	5	8*	26
All	87	136	155	284	125	87	42	916

Table 1. Cross-tabulation of aggression scores at age 10 and age 13 for 916 children.

Note. The ratings can be assumed to be highly reliable.

Chi-square (36) = 245.3, p<0.001

*p<.05 when using adjusted standardized residuals to test for an over frequented cell after Bonferroni correction for 49 tests. Expected values of the four significant cells are 10.2, 15.9, 2.7, and 1.2, respectively.

The Pearson correlation is 0.43 between the age 10 and age 13 aggression ratings. Although researchers are aware of that this is a summary statement of the relationship, nevertheless it is quite common to almost solely rely on the correlation coefficient when interpreting the relationship, often stating something like, "There is a moderate stability of aggression in that high aggression at age 10 tends to go together with high aggression at age 13 and vice versa". This interpretation may be adequate but that depends on the purpose. If it is to understand *individual* development, just a brief inspection of Table 1 shows that, for a substantial proportion of the sample, the statement above does not hold. For instance, for 11% of the children an above average rating at age 10 is combined with a below average rating at age 13, or vice versa; an additional 19% of the sample change their level of aggression from low (1 or 2) to average or from high (6, 7) to average, or vice versa; and only 27% of the children are completely stable.

Coming closer to the individual level, some interesting observations can be made from the cross-tabulation in Table 1. For instance, the strongest stabilities are in the extremes, especially 1>1 and 7>7, and dramatic shifts in aggression are very rare. As an example, it may be of special interest to further study the two children whose ratings increased from 1 to 6. Their changes are very unlikely to have been caused by errors of measurement because the ratings are highly reliable. What happened in their families and school situation to produce this dramatic deterioration? First it was looked at standard demographical variables, like a change in the basic family composition, especially divorce, but there were no changes for the two children. Then it was looked at other school variables, like self and peer rated popularity and school grades, still no pronounced changes. Finally, it was looked for if a hyperactivity syndrome had emerged. This was the case because both children were at age 10 absolutely not hyperactive but at age 10 clearly were so. (Of course, this finding for n=2 is only hypothesis generating.)

To sum up, the findings from analyzing the aggression data exemplifies Molenar's (2004) point that it is dangerous to rely on group statistics when the purpose is to make inferences about individual development. This is warranted only under special conditions.

Average versus individual causality

The second direction towards studying the individual concerns the issue of average versus individual causality. We are all aware of the difficulties in establishing causality in nonexperimental settings and also of the complexity of the causality concept in this case. Nevertheless, it seems reasonable to believe that a careful analysis of good non-experimental longitudinal data can make possible inferences about *average* causality. However, inferences about *individual* causality are another matter and tend to be much more difficult, also in an experimental situation (Bergman, 2009). This is illustrated by the example given below.

In a study of the effects of relaxation therapy for insomnia, Means, Lichstein, Epperson, and Johnson (2000) randomly assigned 28 college students with insomnia to treatment with the remaining 27 students with insomnia forming the control group. Based on diaries kept by the subjects, the self-rated quality of sleep (QUAL) was measured before and after treatment on a scale from 1 to 5, where "5" is "excellent". The average quality of sleep (sd) was reported as seen in Table 2.

Table 2. Comparison between means (SD) in self-rated quality of sleep before and after treatment in the study by Means et al. (2000)

Condition	Baseline	Posttreatment
Treated	3.1 (0.4)	3.4 (0.4)
Untreated	3.0 (0.4)	3.0 (0.4)

The findings were analyzed using MANOVA (the excerpt of results presented here is only a small part of what was analyzed) and the authors drew the conclusion that there was a significant effect of the treatment on QUAL. Their findings indicate that the effect size was close to one sd unit for QUAL among those with sleeping problems and they may have demonstrated average causality. But what about *individual* causality? Almost no information was given in the article that helps in forming an opinion of how many (and which) of the treated students that profited from the therapy and the issue is not discussed by the authors. No reliability estimate was provided for QUAL but a literature search suggests that the reliability of sleep diary data is usually intermediate, that is, in the 0.60 - 0.80 range. The moderate reliability makes it understandable that the authors, like in most therapy studies, restricted themselves to the issue of average causality. Using CTTM, a rough calculation of a 95% confidence interval for a person's QUAL score indicates that it would be around ± 0.4 , which is even somewhat larger than the average difference between baseline and posttreatment. This suggests that for most subjects the individual treatment effect (i.e., the change from baseline to posttreatment) cannot be well estimated (see Feldt, Steffen, & Gupta, 1985; Lord & Novick, 1968 for a discussion of different estimation methods). This is unfortunate because with precise measurements of QUAL and the other dependent variables in the study it would have been possible to find those who did not profit from the therapy and obtain ideas about why this was the case and suggestions for how to improve the therapy.

There have been many studies of individual treatment effects but, in my opinion, they have usually been marred by a lack of reliability in the individual scores. For instance, in the seventies, Cronbach and Snow studied what they called aptitude-treatment interactions in educational settings and, rather discouragingly, they found it hard to establish trustworthy interactions that replicated. Cronbach (1975, p 126), although advocating the importance of the endeavor, talked about "entering a hall of mirrors" pursuing this track. It might be that a major reason for the unclear findings was insufficient measurement reliability.

Methods for studying the reliability of individual treatment effects should be used more often, for instance by applying the Jacobson and Truax reliable change index (RCI) formula (Jacobson & Truax, 1991). However, in most cases the application of such methods can be expected to confirm what has been said above, namely that for most studied subjects no reliable individual change can be detected, unless the reliability of the dependent variable is high or the average treatment effect is very large.

The main conclusion drawn from the above example holds more generally: To study individual causality you normally need precise individual measurements.

The person-oriented approach

The third direction towards studying the individual is the modern person-oriented approach for studying individual development (Bergman & Magnusson, 1997; Bergman, Magnusson & El-Khouri, 2003). In this approach, the focus is on understanding individual development as a dynamic process with bidirectional influences, operating in continuous time and at different levels. It is believed that a crucial aspect of the system under study is its state, characterized by patterns of information in the variables that describe the system. Further, it is proposed that, mostly, only a limited number of such patterns exist which are in some way functional and therefore become typical. Hence, from this perspective it is not natural to treat the involved variables as separate entities in theoretical formulations and analyses. One should instead study the value patterns in the variables as undivided wholes and, for instance, search for typical such patterns.

If the person-oriented paradigm is accepted, it is obvious that reliance has to be placed on individual measurements, which must be reliable for the individual value patterns to be interpretable. It is also clear that standard group statistics will not inform about individual pattern development. However, the common reliance on methods for the classification of observed value patterns into a number of classes or types presents in a different form the problem of summarizing individual development by group statistics. Only if the classes are homogeneous (all members in the class have similar value patterns) can individual class membership inform about individual patterns of development.

Measurements of individuals based on a single original variable vs. based on a scale or index

A frequent measurement issue in many sciences, including psychology, is how to best use the information contained in a number of single original variables that aim at measuring the same concept, either because (1) the variables are very similar (e.g., five questions concern the subjects' degree of satisfaction with their working life in general but they are differently worded) or (2) each single variable covers one aspect of the concept and together they cover the whole concept (e.g., a standardized test in mathematics may consist of several subtests, measuring knowledge of arithmetic, geometry, algebra, and so on). In both cases, the information in the single variables (items) is frequently pooled to produce a new variable that summarizes the information contained in the items. The pooling can be done in different ways, for instance the values in the single variables (items) can be summed or subjected to factor analysis to produce a factor. This type of variable is labeled in different ways (e.g., it is called "a scale", "a factor", or "an index"). In Case (1), a primary reason for constructing a scale is to increase the reliability of the measurement and in Case (2) a primary reason for constructing the scale is to ensure that the scale covers all relevant aspects of the concept. Scales of these types are often used in the social sciences, especially in psychology where methods have been developed for item selection to scales and for weighing the included items. These methods include, for instance, factor analysis, item analysis using classical test theory or item response theory, and methods for studying differential item functioning. Much work has also been done on a more theoretical level, for instance discussing issues of validation and scale level. This psychometric tradition has developed mostly independent of the corresponding work done within statistics and econometrics, and there the term "index" is often used for what in psychology would be called a "scale" or a "factor".

The use of scales is much more widespread in psychology than in official statistics where more commonly results concerning single original variables are reported, as exemplified in the introduction. This is natural because of the different character of the variables with "hard" variables being more common in official statistics but it is also caused by differences between these two disciplines in purposes and types of analysis. It is interesting to note that in psychology a single item is usually considered too unreliable to form an independent or dependent variable in the analyses and most often psychometric methods are used to arrive at a scale. In official statistics you more frequently find published results reporting findings concerning single items, even in the case of "soft" variables. For instance, on the Swedish home page for the Swedish Survey of Living Conditions (SSLC) in November 2009, the only findings that were presented concerned the frequency and intensity of exercise, reported separately for a number of items measuring different types of exercise.

Behind the use of a question formulation and its response alternatives there is always some assumed model of the relationship between the concept of interest and the indicator used to measure it, which is given by the question used. In the above SSLC example, one question was formulated as follows: "I would now like to know how much exercise you get in your spare time. Which one of these response alternatives fits you best?" (my translation). There were five response alternatives with the lowest level of exercise being labeled "Get almost no exercise at all" and the highest level of exercise labeled "Exercise regularly rather intensively at least two times a week". The concept of interest might for many users be something like "the amount of exercise of a type that tends to increase aerobic physical fitness". If this concept is treated as a latent variable (denoted with F) and the indicator, based on the responses to the question is denoted with f, two conclusions are apparent: (1) There are many possible f:s that could be used to measure F and (2) the assumptions one can make about the relationship between f and F decide how findings based on f can be interpreted and how f can be used in the analyses. Consider the following three assumptions of the relationship between f and F:

- 1. f = F + e, where e is a random error, same function assumed for all individuals.
- 2. f = aF + b + e, where a and b are constants, same function assumed for all individuals.
- 3. $f = a_iF + b_i + e_i$, where the subscript indicates individual i.

It is obvious that Assumption 1 is very strong and not likely to hold for the exercise example. This conclusion holds in most contexts. To give another example: For many decades, surveys have been carried out concerning the Swedish population's attitude for or against nuclear power and, within a given time period, the percentage reported to be positive to nuclear power varied substantially according to the institute that performed the survey due to minor differences in the formulation of the question and of the response alternatives (see e.g., Holmberg & Pettersson, 1980; Johansson, 2002).

Assumption 2 is less stringent and it can be sufficient for making comparisons between groups and time periods, which often is the primary purpose. (If only the relaxed Assumption 3 is made you have to consider individual differences in the response functions that easily get confused with random errors and the interpretation of the findings become complex; Saris & Gallhofer, 2007).

The line of reasoning presented above is simplified but it serves to illustrate that the assumptions you can make about the form of the relationship between the indicator and the concept should decide how the findings are interpreted and what analyses are appropriate. Of course, considerations of the model for the indicator-concept relationship could be disregarded and the researcher could instead just carefully present what has been measured, leaving such considerations entirely to the consumer of the report. However, if the measurement properties of the indicator have not been carefully discussed in the report (e.g., in relation to other possible indicators) the consumer often has difficulties in interpreting the findings. In the SSLC example, such considerations were not presented in the report the home page was linked to.

As pointed out above, in most cases within psychology where a concept is to be captured by measurements, psychometric methods are used to develop a scale based on the responses to many items. This is done to increase the reliability but also to extract the common core of them in the form of a scale by triangulation of the information in the items. However, for both good and bad reasons, there seems to be a certain reluctance within official statistics to rely on psychometrically constructed scales. Although the standard psychometric approach in many contexts is sound, it has often led to that in psychology comparatively less emphasis is given to a thorough analysis of the information contents of the single item isolated from the information contents of the other items. This is in contrast to what is the case within, for instance, good survey research practice. There single questions are often carefully tested, for instance using cognitive laboratory procedures (see e.g., Bergman, 1994 for an overview). Such a test is usually highly informative and leads to an improved questionnaire where a number of "bad" questions have been weeded out or reformulated to remove ambiguities in wordings, and the test increases the chances that the concepts targeted by the questionnaire designer match the way the respondents interpret the questions.

Discussion

In some fields of psychology, it is essential that single individuals' measurements can be interpreted so that inferences can be made about, for instance, individual development. This is in contrast to official statistics where the focus rarely is on interpreting single units' measurements but rather on providing estimates of population parameters like percentages in different categories, means or correlations. These are the dominant forms of statistical reporting. Nevertheless, the importance of paying more attention to single units' measurements also in official statistics may be underestimated, see Bergman (2010).

It has been argued that to obtain findings interpretable at the individual level, precise measurements are necessary. In contrast, when the focus is on interpretation at a group level, presenting findings in the form of group statistics are usually sufficient. In this case, statistical models can under certain assumptions handle substantial errors of measurement in the studied variables; errors that would make such variables unusable for studying the individual. In fact, most variables in current use in psychology are not sufficiently reliable to allow for the study of the individual, as exemplified in this article. To provide a view from outside psychology of the importance of precise measurements, Bergman and Vargha (2013) presented the following simile, taken from astronomy:

Some 500 years ago a good model emerged of the orbits of the planets in our solar system, explaining the movements in time of each single planet. The data used to develop this model were precise measurements of different kinds. Suppose these data had contained errors of measurement of the size we commonly have in psychology. Then a crude estimation of the standard error of measurement of a planet's distance to the sun in AU units is of the magnitude 3 AU (corresponding to a reliability of about 0.90). In this case the relative distances of the four inner planets to the sun would be completely blurred since their distances range from 0.4 AU to 1.5 AU. It is then highly unlikely that the modern model of the orbits would have emerged.

Admittedly, the cited simile is somewhat halting but it provides an additional example of the quagmire a researcher encounters if he/she tries to construct a model explaining single observational units' behavior using unprecise measurements.

In many types of statistical analyses, the handling of outliers is problematic. Are they valid values or have they been caused by errors of measurement? The answer to this question can be important for deciding whether an outlier should be included or excluded from an analysis. Precise individual measurements are helpful in this decision process.

Measurement issues cross discipline borders and are to a fair degree almost universal. Hence, measurement technique research should also sometimes be multi-disciplinary, including collaboration between, for instance, psychometricians, statisticians, econometricians, cognitive scientists, and chemotricians. In addition to probable synergy effects. this would also lead to an exchange of valuable measurement techniques between disciplines. For instance, it was pointed out that psychometricians might find useful the cognitive laboratory methods for testing questions that have been developed in survey research. Within that field, methods have also been developed for testing question formulations by the use of split-ballot experiments that could be used more in psychology (Shuman & Presser, 1981). From a Swedish viewpoint, it is interesting to note that there is a research unit at the Department of Applied Educational Science. Umeå University that specializes in methods for educational measurement and that can serve as a clearing house for related measurement issues in the behavioral sciences.

To sum up, in contexts where individual measurements are to be interpreted, high measurement precision must be given priority and taken into account in the research design. Of course, this comes at a price. Most standard measures in psychology are not very reliable and new measures with high reliabilities may be quite difficult to construct. It might lead to that only a reduced number of variables can be included and a smaller sample size studied than would have been feasible if only group analyses were the purpose. It is also a scientific loss if the researcher cannot use established instruments for which a body of research findings already exists. Nevertheless, increasing measurement precision deserves to be given a higher priority than is the case today.

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