Rasch Measurement Instead of Regression

Benjamin D. Wright, University of Chicago
Kyle Perkins, Southern Illinois University
J. Kevin Dorsey, Southern Illinois University

This paper illustrates the use of Rasch measurement as an alternative to regression analysis to identify gout and non-gout patients who do and do not fit a gout variable constructed by the Rasch model. Unlike a numerical regression coefficient report, the clinician benefits from the one clear picture of the relationship among laboratory values and gout diagnosis which the Rasch model constructs.

The purpose of this paper is to demonstrate how a Rasch measurement model can be used to identify and describe the relationships among laboratory abnormalities among patients who have and have not been diagnosed with gout. Rasch analysis constructs a mathematical model of a gout variable, which identifies blood chemistries which co-occur and measures their utility as gout predictors. The model identifies patients whose pattern of blood chemistries do and do not fit the model. The purpose of this paper is to show how a blood chemistry profile can be organized to make a patient's diagnosis specific blood status immediately apparent to the clinician.

The Measurement Model

Rasch measurement construction applies a stochastic Guttman model to convert dichotomous, interval, and rating scale observations into linear measures (to which linear statistics can be usefully applied) and tests for goodness-of-fit to validate its item calibrations and patient measures. The basic fit statistic is a ratio of observed residual variance to expected residual variance and is near 1.00 when observed variance is comparable to expected.

In this application the Rasch model combines calibrations of blood chemistry items additively to patient measures to define observation probabilities. This stochastic conjoint additivity specifies a Guttman scale of probabilities to which the data are fit stochastically.

Rasch measurement estimates each parameter independently of all other parameters because its sufficient statistics exhaust all information in the data, which is associated with each parameter.

The unidimensional linear continuum to which the Rasch model fits the data provides estimates of item calibrations and patient measures which are not affected by the distributions of items or patients. Patient measures are test-free because their estimates are adjusted for the difficulty distribution of the items reported for that patient. All estimates are expressed in linear measures on a common scale defined by a single latent variable (Wright, 1999; Wright & Stone, 1971).

The Variables

Risk factors for gout have been studied intensively. The risk factor items used in this study are: uric acid, gender, age (at gout diagnosis), the presence or absence of diabetes, hypertension, kidney stones and diuretics, weight, height, body surface area, uric acid, cholesterol, triglycerides, urea nitrogen and creatinine.

Gout is a heterogeneous group of genetic and acquired diseases characterized by the deposition of monosodium urate monohydrate crystals in a joint. Alcohol, surgery, or trauma can trigger gout (Wolfe, 1991). Gout is chiefly a disease of men. Peak incidence occurs between ages 30 and 50 (Harris et al., 1999).

Further medical information can be found in Acheson et al., 1966; Berger & Yu, 1975; Campbell, 1988; Culleton et al., 1999; Evans et al., 1968; Garrick et al., 1972; Gibson & Grahame, 1974; Glynn et al., 1983; Murphy et al., 1982; Roubenoff, 1990; Roubenoff et al., 1991; Wolfe, 1991; Wolfe & Cathy, 1991; and Wyngaarden, 1988.

Method

Patient Selection

The computer records of a multi-specialty group practice were searched for patients with a gout diagnosis who had an office visit during a nine-month period. Of 91 charts available for review, 48 patients had information for all items under investigation.

Forty-eight patients without gout who had multi-channel chemistry profiles during a previous three-month period were matched pairwise by gender and age to the 48 gout patients.

Chart Review

At the first attack of gout, patients' gender, age, height, weight, urea nitrogen, creatinine, blood pressure, treatment with diuretics, and presence of insulin or non-insulin dependent diabetes mellitus were recorded. Kidney Stones were considered present if documented at any time in the patient's chart. Uric acid values were obtained while the patient was asymptomatic and not receiving allopurinol or uricosuric therapy. Cholesterol and triglyceride values were obtained after an overnight fast. Ninety-six observations were submitted for analysis: forty-eight gout and forty-eight non-gout patients, each observation having values recorded for the previously mentioned items.

Uniform Data Coding

For blood chemistries in mg/dl, height in inches and weight in pounds, each physical science metric value X was recoded linearly to nearest integer codes:

$$Y=9(X-MIN)/(MAX-MIN)$$

This coding simplifies the physical science metrics to 10 equal size steps labeled 0 through 9. The resulting codes are co-linear with the original physical science variables. (Table 2 gives the codes for uric acid, urea nitrogen and creatinine.)

Analysis

The data are analyzed by the WINSTEPS Rasch Analysis computer program (Linacre & Wright, 2000). WINSTEPS examines the complete data set, calculates fit statistics for each diagnostic item, uses a component analysis of data residuals to identify significant relationships among the diagnostic items and deletes items which do not contribute useful information. The result is the best linear variable for predicting gout, which these data support.

Results

Fifteen items of medical record information were provided for 96 patients. Forty-eight of the patients are a typical sample of patients diagnosed to have gout. The other 48 patients were selected so that each gout patient was matched by another patient similar in age and in gender but without a gout diagnosis.

Since our purpose is to explore the utility of a new way to analyze and display these kinds of data, we set aside prior expectations as to which information is supposed to predict gout. Instead, we begin our analysis with an open mind to find out how well this new method of analysis, implemented by WINSTEPS, can discover the best ways to predict gout from these data without cueing as to which patients are supposed to have gout and then to display this prediction in a graphical way that is clinically useful.

Unlike the regression approach, we do not use the presence/absence of a gout diagnosis as a "dependent variable" by which to narrow the combined effects of other, "independent variables". WINSTEPS can do this by anchoring patients on their gout diagnosis. But, for this article, we show instead what WINSTEPS can discover without being cued to detecting gout as its only object. We use WINSTEPS to look for the most general combination of the available medical record information, which maximizes a single measurement separation of these 96 patients, independent of their gout diagnosis.

We begin with all 15 original medical information items and step-by-step set aside items, which WINSTEPS misfit analysis shows are inconsistent with the construction of a single measure. The final steps in this process are reported in Table 1.

Table 1. Successive Deletions of Most Misfitting Blood Chemistry Item

INFIT MNSQ	INFIT ZSTD	MISFIT OUTFIT MNSQ	ORDER OUTFIT ZSTD	ITEM
		STEP	ONE	
1.29	1.90	*1.31	*2.0	Cholesterol
1.15	0.70	0.89	-0.5	Triglycerides
0.90	-0.50	0.95	-0.2	Urea Nitro
0.79	-0.90	0.79	-0.9	Creatinine
0.77	-1.80	0.78	-1.7	Uric Acid
		STEP	TWO	
1.47	2.10	*1.41	*1.30	Triglycerides
0.81	-0.80	1.06	0.20	Creatinine
0.84	-0.80	0.89	-0.60	Urea Nitro
0.75	-1.90	0.69	-2.40	Uric Acid

Note. * indicates deleted variables.

At each step we examine an item component factor analysis of data residuals to monitor dimensionality. By the time we have reduced our number of items from 15 to 11, it becomes obvious that surface, weight and gender imply a different measure for these patients than the four remaining blood chemistry items.

Figure 1 [WINSTEPS Table 23.2], "Finding the Variables from Rasch Residual Principal Components", shows the results of a principal component factor analysis of data residuals from the best single measure the 11 remaining items can support. The plot of item factor loadings against item measures shows a clear separation of male corpulence, clustered at the top of Figure 1, from the blood chemistries, clustered at the bottom. The location of a gout diagnosis in the center of the blood chemistry cluster at the bottom of Figure 1 implies that blood chemistry may provide better information about gout and also hypertension and a diuretic regimen than male corpulence among these 96 patients.

We could develop two measures of "gout", one based on male corpulence and another based on blood chemistry. This article is about the four blood chemistries appearing at the bottom of Figure 1.

During the step-wise analysis of the five blood chemistries shown in Table 1, WINSTEPS reports that the separation of patients by measure is improved by setting aside cholesterol and triglyceride information. After triglyceride is removed from the measurement model, Creatinine emerges as the next least informative blood chemistry item. We could set

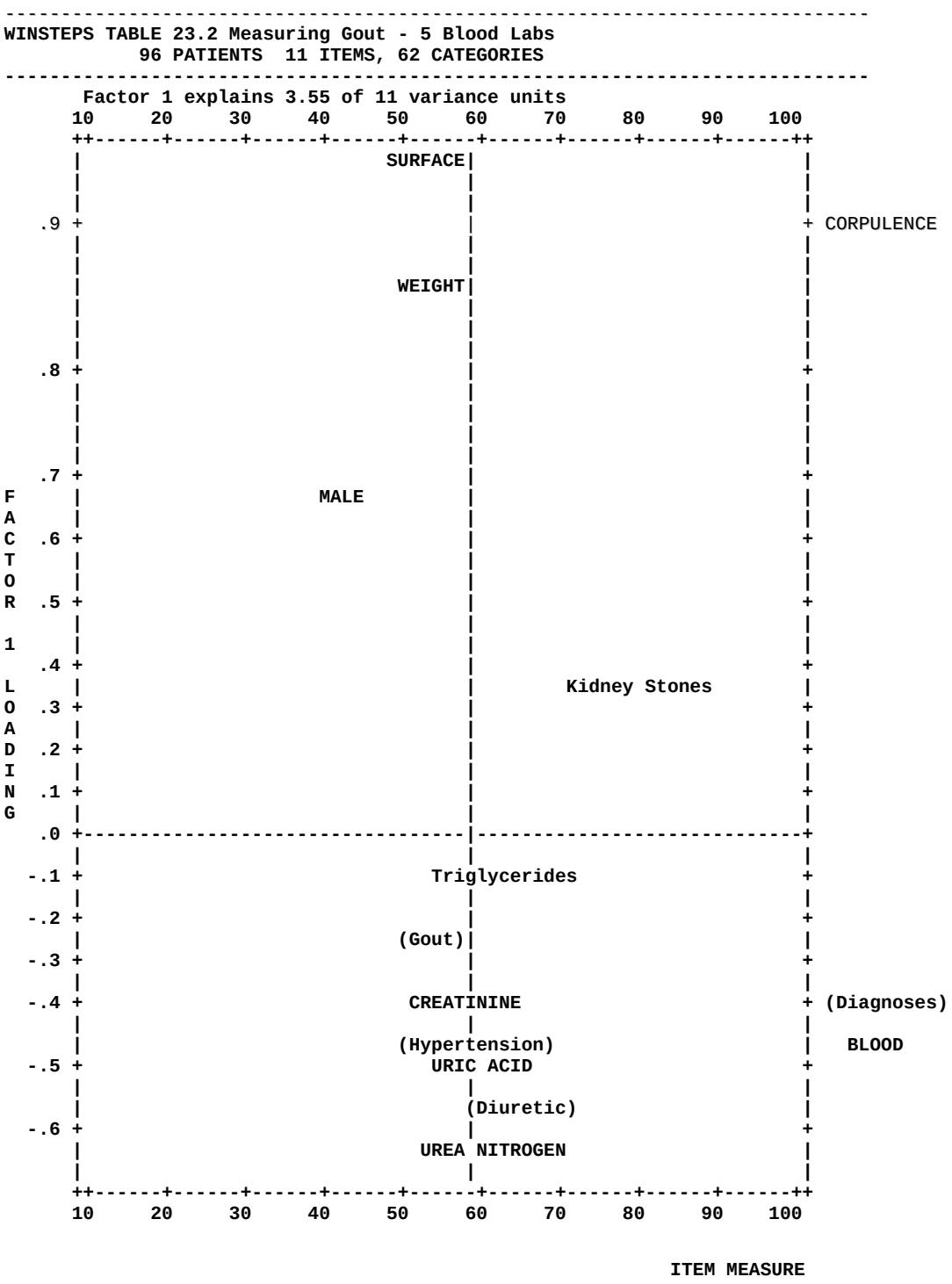

Figure 1. Finding the Variables from Rasch Residual Principal Components

```
-------------------------------------------------------------------------
WINSTEPS TABLE 2.2 Measuring Gout from 3 Blood Tests
      96 PATIENTS, 4 ITEMS, 32 UNIFORM CATEGORIES
-------------------------------------------------------------------------

EXPECTED SCORE: MEAN  (":" INDICATES HALF-SCORE POINT)
10   20    30    40    50    60    70    80    90   100
|-----+-----+-----+-----+-----+-----+-----+-----+-----|    BLOOD TEST
0   1 :    2       :     3    :(4):5:6: 7: 8  :   9   9   Urea Nitrogen
|                                                         |
0    1   :   2   :  3  :  4 :(5) 6  :  7  : 8  : 9    9   Uric Acid
|                                                         |
|                                                         |
0    0    :        1     :   (2) : 3:45:67:8  : 9     9   Creatinine

0                   NO    :   (YES)                     1     GOUT?

|-----+-----+-----+-----+-----+-----+-----+-----+-----|
10   20    30    40    50    60    70    80    90   100

    1           1     3  5 65 87 31121 21 1        PATIENTS WITH GOUT
                 T     S     M      S     T

                1
       2  3   2  0   5 9  8 51 11 1                PATIENTS WITHOUT GOUT
         T     S     M      S     T
```

Figure 2. The Complete Story on One Page

aside creatinine and concentrate on uric acid and blood urea nitrogen. But analysis with and without creatinine produces statistically equivalent results, and creatinine results dramatize an important finding concerning the non-linear relation between chemical measures and their medical implications. We establish a new medical variable defined by the observed relationships among the three blood chemistries: uric acid, urea nitrogen and creatinine.

Figure 2 [WINSTEPS Table 2.2], "The Complete Story on One Page", shows the resulting definition and patient discrimination of a gout diagnosis. This definition of a blood chemistry gout variable based on laboratory measures of uric acid, urea nitrogen and creatinine provides a compelling patient chart for the clinician.

Figure 2 puts the diagnosis of gout from patient chemical values of these three blood chemistries onto a simple, easy to read chart which lays out all of the blood chemistry information for this medical variable and also shows where each of the 96 patients measure on this variable. This chart makes visible in complete context the relation between the diagnosis of gout (the dependent variable in a regression analysis) and the predictive efficacy of the three blood chemistry variable (the independent variables in the regression analysis). The differences between this analysis and regression is that all results are visualizable on a common linear metric and no results are contaminated by missing data or sample dependent covariance.

The three top rows of 0-9 integers in Figure 2 mark out the medical measure positions of 10 equally spaced mg/dl chemical levels as they were coded uniformly into integers 0-9. Table 2 lists the mg/dl values linearly represented by each of these 0-9 codes. The vertical alignments of the codes in Figure 2 mark the mg/dl values of the three blood chemistries which match in their relative strength of "gout" implication. The integer codes for mg/dl values which the 1997 Merck Manual specifies as "too high" are in parentheses.

The fourth row of Figure 2 marks the predictor positions on this medical measure of the observed "Gout?" diagnosis: NO or (YES). The colon between NO and (YES) at a blood chemistry measure of 53 marks the point at which the estimated odds for "Gout?" are an even, 1 to 1. Estimated gout odds can be calculated for any measure position from 10 to 100 because on this scale each increment of 9 units triples the odds that a patient has gout. For example, since the estimated odds at blood chemistry measure 53 are even, the estimated odds become 3 to 1 at 53+9=62 and 9 to 1 at measure 71. In the other direction, the estimated odds for gout drop to 1 to 3 at 53-9=44 and 1 to 9 at 35.

Table 2. Variations in Medical Implications for Equal mg/dl Increases in Creatinine

Uniform Coding of Blood Chemistry Levels in mg/dl

Uniform Code	Uric Acid mg/dl	Urea Nitrogen mg/dl	Creatinine Mg/dl
0	2.10	00	0.7
1	3.30	05	1.0
2	4.50	10	1.3
3	5.70	15	1.6
4	6.90	20	1.9
5	8.10	25	2.2
6	9.30	30	2.5
7	10.50	35	2.8
8	11.70	40	3.1
9	12.90	45	3.4

Medical Measure Changes Implied by Equal mg/dl Increments of Creatinine

mg/dl Change	Code Change	MedMeasure Change	Mg/dl per MedMeas Unit
0.3	0-1	22	0.0136
0.3	1-2	18	0.0167
0.3	2-3	8	0.0375
0.3	3-4	3	0.1000
0.3	4-5	1	0.3000

In Figure 2 the horizontal spacing of all reference points and measures is uniformly linear in units of medical importance. (The uneven spacing of codes 0 to 9 in Figure 2 shows that these medical implications units are not collinear with the original chemical mg/dl units). This medical spacing enables rapid visual evaluation of the medical distance of any patient measure to the left or right of the colon at blood chemistry measure 53 to be sufficiently accurate for clinical purposes and even faster and less error prone than juggling odds.

When a patient's blood chemistries measure them below the "NO" at 44, we can advise them with some confidence that their blood chemistry does not imply gout. When, on the other hand, their measure exceeds the "(YES)" at 62, then our advice would have to be otherwise. We can show them their own position on the "Gout?" blood chemistry chart so that they can see for themselves where they stand with respect to a blood chemistry diagnosis of gout.

Because the WINSTEPS chart in Figure 2 maps the medical implications of the relationship between blood chemistry and "Gout?" probability in easy-to-read equal spacing, clinicians can find it easy to discover in their own practice where the best turning points are for the decisions their practice teaches them to make.

The "Gout?" diagnosis row serves the same purpose as gout predictions derived from a regression analysis. In this application, however, the prediction is no longer twisted by the incidental vagaries of missing data or the sample distribution dependence of independent variable covariance.

The first row at the bottom of the figure shows the measure positions of each of the 48 gout patients and right below that the measure positions of each of the 48 gender and age matched, but not gout, patients. This provides a linear visualization of the dependent variation identified by this analysis – information seldom provided in a regression report.

On this simple linear chart, the extent to which this three-blood-chemistry measure separates these gout and "not-gout" patients is obvious. The means of the two patient groups, marked by "M's" at blood chemistry measures 45 and 60, are statistically distinct. That may be nice to publish, but clinically the visible position of each individual patient on this blood chemistry variable is far more useful.

All measures, indeed all inferences, are inevitably qualified by margins of error. We expect a region of overlap, like the one around the gout colon between 50 and 58. The vertical alignment of the "Gout?" diagnosis "(YES)"with the parenthesized Merck Manual reference values is clear evidence of the coherence between these statistical results and established reference values – an easy to see verification of validity.

Among the gout patients in Figure 2, there are two at blood chemistry measures 16 and 39. These blood chemistry measures are sufficiently low to suggest that, if these patients do have gout, it has symptoms other than blood chemistry.

Among the not gout patients there are three with blood chemistry measures in the 60's, a suspicious level according to our measure and also according to Merck.

If we use these 96 patients as current norms for this kind of gout measurement, then we can see and explain the implications of each measure position in terms of the observed odds among these 96 patients for (or against) having gout.

At blood chemistry measure 57, the observed gout odds among these patients are 6/5, just about even. At measure 64, however, observed gout odds rise to 7/1, or, if we group adjacent columns, (7+3)/(2)=5/1. These odds for the presence of gout are large enough to suggest a decision. Moving down to a measure of 52 implies gout odds of 5/8 and at measure 49 odds of only 1/3. At lower measures the observed odds against gout become overwhelming.

Even this small sample of 96 provides preliminary norms. A simple accumulation from medical records of a larger and continually growing sample will provide observed gout odds interpretations of any medical measure with increasing authority.

A final, perhaps surprising and, if so, crucial, observation clearly visible in Figure 2 and calculated in Table 2 is the non-linearity of the relationship between mg/dl chemical metrics and the metric of medical diagnosis. This non-linearity shows in the unequal medical measure distances between the integer codes which mark equal increments in chemical mg/dl.

Table 2 shows that for creatinine, the increment in diagnostic significance from code 0, marking 0.7 mg/dl, to code 1, marking 1.0 mg/dl is 22 medical units. This is .0136 mg/dl per medical measure unit. If we use 5 medical diagnosis units as our margin of error, then creatinine changes as small as .07 mg/dl could have medical implications at levels below 1 mg/dl. But the increment in medical significance from code 4, marking 1.9 mg/dl, to code 5, marking 2.2 mg/dl, is only one medical unit, or 0.3 mg/dl per medical measure unit. This means that at creatinine levels near 2 mg/dl it takes a change of 1.5 mg/dl in chemical creatinine to mean as much medically as a change of 0.07 mg/dl at levels near 1 mg/dl. The chemical mg/dl increase at codes 4 to 5 is 22 times the increase at codes 0 to 1. This implies that mg/dl increases in creatinine below 1 mg/dl are 22 times more important medically than the same size increases above 2 mg/dl. These numbers are listed in Table 2. A regression analysis is unlikely to document or even to reveal such an important finding.

Discussion

This paper shows how Rasch measurement can replace regression analysis to advantage and also provide reports far more useful to medical diagnosis. The practical implications of regression coefficients are hard to visualize, let alone understand. In addition regression coefficients are vulnerable to missing data and disturbed by sample dependent covariance. The results reported here show how the intentions of regression analysis can be better realized and more usefully reported by Rasch measurement.

This paper shows how Rasch analysis can simplify the clinician's job by constructing one simple picture from which the implications of laboratory abnormalities can be clearly seen. The illustration is based on observed relationships among laboratory findings among patients who have been diagnosed with gout by the usual methods. The analysis shows that the gout implications of corpulence can be quite distinct from blood chemistry and that cholesterol and triglycerides do not contribute useful information to a gout blood chemistry variable.

References

Acheson, R.M., & O'Brien, W.M. (1966). Dependence of serum-uric-acid on haemoglobin and other factors in the general population. *Lancet, 2*, 777-778.

Berger, L., & Yu, T-F. (1975). Renal function in gout: IV. An analysis of 524 gouty patients including long-term follow up studies. *American Journal of Medicine, 49*, 605.

Campbell, S. M. (1988). Gout: How presentation, diagnosis, and treatment differ in the elderly. *Geriatrics, 43*, 71-77.

Culleton, B. F., Larson, M. G., Kannel, W. B., & Levy, D. (1999). Serum uric acid and risk for cardiovascular disease and death: The Framingham Heart Study. *Annals of Internal Medicine, 131*, 7-13.

Evans, J. G., Prior, I. A. M., & Harvey, H. P. B. (1968). Relation of serum uric acid to body bulk, hemoglobin, and alcohol intake in two South Pacific Polynesian populations. *Annals of the Rheumatic Diseases, 27*, 319-325.

Garrick, R., Bauer, G. E., Ewan, C. E., & Meale, C. F. (1972). Serum uric acid in normal and hypertensive Australian subjects. *Australian New Zealand Journal of Medicine, 4*, 351-356.

Gibson, T., & Grahame, R. (1974). Gout and hyperlipidaemia. *Annals of the Rheumatic Diseases, 33*, 298-303.

Glynn, R. J., Campion, E. W., & Silbert, J. E. (1983). Trends in serum uric acid levels 1961-1980. *Arthritis and Rheumatism, 26*, 87-93.

Harris, M. D., Siegel, L. B., & Alloway, J. A. (1999). Gout and hyperuricemia. *American Family Physician, 59*, 925-934.

Linacre, J. M., & Wright, B. D. (2000). *WINSTEPS Rasch Analysis Computer Program*. Chicago: MESA

Murphy, M. B., Lewis, P. J., Kohner, E., Schumer, B., & Dollery, C. T. (1982). Glucose intolerance in hypertensive patients on prolonged diuretic treatment. *Lancet, 2*, 1293-1295.

Roubenoff, R. (1990). Gout and hyperuricemia. *Rheumatic Diseases Clinics of North America, 16*, 539-550.

Roubenoff, R., Klag, M. J., Mean, L. A., Liang, K. Y., Seidler, A. J., & Hochberg, M. C. (1991). Incidence and risk factors for gout in white men. *Journal of the American Medical Association, 226*, 3004-3007.

Wolfe, F. (1991). Practical therapeutics – gout and hyperuricemia. *American Family Physician, 43*, 2141-2150.

Wolfe, F., & Cathey, M. A. (1991). The misdiagnosis of gout and hyperuricemia. *Journal of Rheumatology, 18*, 1232-1234.

Wright, B. D. (1999). Fundamental measurement for psychology. In S. E. Embretson & S. L. Hershberger (Eds.), *The New Rules of Measurement. What Every Psychologist and Educator Should Know* (pp. 65-104). Mahwah, NJ: Erlbaum.

Wright, B. D., & Masters, G. N. (1982). *Rating Scale Analysis: Rasch Measurement.* Chicago: MESA Press.

Wright, B. D., & Stone, M. H. (1971). *Best Test Design: Rasch Measurement*. Chicago: MESA Press.

Wyngaarden, J. B. (1988). Gout. In J. B. Wyngaarden & L. H. Smith, Jr. (Eds.), *Cecil Textbook of Medicine* (18th ed.) (pp. 1161-1170). Philadelphia: W. B. Saunders Company.