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A MODEL FOR PSYCHOMETRICALLY DISTINGUISHING APTITUDE FROM ABILITY

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A Model for Psychometrically Distinguishing Aptitude from Ability

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It is widely agreed that current ability measures reflect a complex interaction of environmental and genetic factors. The literature on general intelligence, for instance, has unequivocably demonstrated that test performance is highly influenced by the culture or sub-culture the individual is a member of, such as race and socio-economic status. Although the controversy still rages as to whether these sub-cultures differ genetically (Herrnstein, 1971; Jensen, 1969), it is known that exposure to more advantageous environments will increase I.O. estimates. (cf. Lee, 1951). Thus, with general intelligence and probably many other abilities, the particular learning experiences and opportunities an individual encounters has a fairly large influence on his estimated ability. This leads to a basic measurement problem since individuals with different potentials may show the same estimated ability when their learning experiences have varied widely. The problem is to find a method of determining which individuals have undeveloped potential so that more appropriate selection criteria or educational intervention may be given to these individuals.

The major purpose of the present paper is to present a method which may hold some promise in psychometrically distinguishing ability (current status on a test) from aptitude (potential). Tests measuring cognitive ability factors have not, as yet, been developed to the point where the general utility of this approach can be assessed. However, data from a psychomotor ability will be presented in this paper to explore the feasibility of the approach and to suggest ways to solve some of the more practical problems in application of the technique.

A Conceptualization of the Relationship of Ability to Aptitude

At the conceptual level, it is suggested that ability be defined as current status and aptitude be defined as potential status under environmental conditions optimally favorable to the development of the ability. Assessment of aptitude, then, would imply equivalent learning experiences for all individuals. Obviously, this is not the case, but it is assumed that it is possible to distinguish between individuals having the same ability but with different potentials, by directly measuring the modifiability of estimated ability. That is, the individual with the greater aptitude should show a faster rate of change on estimated ability when given intervention than a person with lesser aptitude but within the same current level of ability.

It should be noted that this approach is different from previous research on gain scores. Woodrow (1939), for instance, defined learning ability as a general characteristic, without respect to level of current ability status. Woodrow found that change over practice, assumed to be learning ability, was task specific and did not correlate well with more general ability factors. As has been summarized elsewhere (Jones, 1969), it is often the case that rate of change correlates negatively with initial status. That is, those changing the most are the ones showing the poorest initial performance. Thus, it is assumed that modifiability of measured ability will not be a meaningful measurement unless initial status is partialled out or controlled. As suggested by Cronbach & Furby (1970) a "residualized gain score" can be used to select those who perform better on the post-test measure than was expected from the pre-test measure.

It is hypothesized that psychometric relationships between ability, aptitude, and modifiability can be modeled after the equation for a straight line, $y = a + bx$. The symbols in the equation are defined as follows: 1) the constant, a, is the initial status on the ability test; 2) bx is the modifiability of the ability test score; and 3) y is the aptitude when measured ability is at asymptotic value. Modifiability has two separate components. One of these, x, refers to either the graded quality or amount of intervention between ability estimates, while b refers to the rate of ability change observed on repeated testings. An individual's ability, then, is conceived of as a fluid quantity, characterized by both his initial status, a, and sensitivity to intervention, b. It is assumed that initial status and modifiability are additive with respect to aptitude.

It follows, then, that in order to have a measurement which reflects aptitude, it is necessary to use two scores, current status and modifiability. Minimally, this necessitates two measurements of ability, one before and one after a standardized intervention (fixed value of x). For prediction, these two scores would be two different independent variables in a multiple regression equation, weighted according to the relative importance of modifiability and current ability status in the criterion to be predicted. When modifiability is measured by a raw gain score, the beta weight corresponding to raw gain score is equal to the correlation between the residualized gain score and the criterion divided by the degree to which gain is independent of status.[1] When gain and initial status are negatively correlated, the correlation of residualized or unexpected gain to the criterion is positive (those changing faster than expected by initial status scores perform better on the criterion). It should be noted that gain may not correlate at all with the criterion, while the residualized gain may have a strong correlation with the criterion. Thus, raw gain may have a suppressor effect in prediction through its correlation with initial status.

There are several questions which must be answered with regard to the feasibility of utilizing such an approach to prediction. The first, and most obvious, concerns the extent to which ability scores show gains from very short intervention periods. Previous studies on coaching (cf. Anastasi, 1958, for summary) indicate that large gains can be made, and that there are individual differences with respect to gains. Apparently students from the most deficient environments show the largest gains. It is not clear, however, whether this is due to the correlation of gain with initial status or if there are also larger unexpected gains for such a group.

A second question concerns the relationship between the modifiability of the test score and the latent ability trait. Basically, this question concerns the relationship between the asymptotic value obtained on the predictor to the latent aptitude. In the long run, the degree of correspondence here will be determined by the extent to which modifiability scores lead to increased predictability of achievement. However, in the short run there is a design problem with respect to the degree and nature of the standardized intervention. For instance, little correspondence between latent aptitude and asymptotic test score would be expected when the intervention uses the same items that are used for final testing. The asymptotic test score would be highly dependent on rote memory rather than aptitude.

A set of related questions concerns the use of any kind of rate measure in addition to initial ability to provide increased reflection of aptitude. The most critical of these concerns the relationship of rate measurements to the true shape of the individual ability curves. Most likely, this curve is S-shaped such that slope between any two points varies over the course of intervention. If initial status is near the bottom of this curve (large undeveloped potential), the instantaneous rate (derivative) will start out at a low level and then increase to a maximum rate, then followed by a decrease in rate until asymptotic value is obtained. Thus, it is not necessarily the case that between individuals at the same initial status, the one with the highest ability will have the highest modifiability. It depends on what point of the curve is being observed.

Figure 1 presents ability curves and observed rate of change for two hypothetical individuals. Two individuals may have the same average rate of change (observed between two distance points over intervention) when one has a decreasing instantaneous rate and the other an increasing rate. The one with the increasing rate (Person 2) will reach the higher asymptotic level, but this will not be detectable by gain between these two points.

There are at least two possible approaches to this problem. One is to take several slope measurements over increasingly better interventions. This may be impractical because it is time-consuming for complex abilities and may have insurmountable difficulties with respect to precision of measurement of ability scores. A second approach is to use only one level of intervention, but to select this intervention such that the reflection of aptitude by modifiability is maximized in the measurements. In the section that follows, molar correlation analysis (Jones, 1962; 1970a) is used on some psychomotor data to demonstrate how this selection may be maximized in a population of individuals.

A final question concerns how rate is to be computed. If a single intervention is used, observing ability only twice, there is no obvious unit to use on the abscissa. When rate is to be used in a regression equation with initial status, there are three basic possibilities: 1) slope, 2) score ratio and 3) gain score. To compute the first rate index, slope, some sort of measurement of performance must be taken during intervention. It may be feasible to generate such measures, such as time spent in practice, but the intepretability is not always clear. The second possibility, score ratio, can be used on tests providing ratio scale measurements. Although no currently existing ability test provides ratio scale measurements, there are new scaling methods (cf. Wright, 1969) which can potentially allow score ratios to be computed for an ability test. The third possibility is to compute a raw gain score. Since the use of the gain score is to be in a regression equation, as proposed above, many of the objections to raw gain scores are eliminated.

However, no matter which computation of rate is used, the reliability of these measurements from equivalent forms should be directly considered during the test development phase of ability tests. To depend on tests developed according to classical criteria of reliability leads to paradoxes in estimating the reliability of rate scores. That is, gain is not independent of measurement error.

Information on the general utility of this approach on complex cognitive abilities apparently must wait for further development. However demonstration data on a psychomotor ability are presented below to illustrate the relationship of modifiability to prediction and to suggest internal criteria for the selection of a level of intervention.

The Predictability of Motor Reversal Performance

Materials. A task which reflects spatial reversal ability, tracing a simple figure in a mirror-blind apparatus, was used to provide ability status and modifiability measurements. In the mirror-blind apparatus, the only visual cues are completely reversed from normal eye-hand coordination tasks. This task has been shown to be highly influenced by experience, although individual differences do persist (P. W. Fox, personal communication). The figure to be traced for the predictor measurements was a "zig-zag" line that required reversals in only two different directions. Both reversals were at 45 degree angles.

The criterion task to be predicted by these status and modifiability measurements was the tracing of a more complex figure in the mirror-blind apparatus, a six-pointed star. The star was constructed such that the role of spatial reversal ability would be operationally maximized and task overlap between the zig-zag line and the star with respect to specific reversals would be minimized. On the star, no two reversals were in the same direction at the same angle. Also, none of the reversals on the star was in the same direction as on the zig-zag line. To equate the role of motor speed on these tasks, the star and zig-zag line were equated for total number of reversals and distance between reversals. The resulting correlations between the predictor measurements on the zig-zag line and the criterion star should then be due to how well both measurements reflect motor reversal ability. The general question asked in the data, then, is as follows: does modifiability on a specific indicator of an ability (similar to coaching on a test with homogeneous items) add anything to the prediction of a complex task assumed to load heavily on the ability? If so, then modifiability on the zig-zag line should add to the predictability of the star, in the mirror-blind task.

<u>Subjects and procedure</u>. The subjects were 49 college sophomores enrolled in elementary psychology courses at the University of Minnesota. Four subjects were dropped from the experiment; two because of equipment failure, one for exceeding the five minute time limit, and a fourth one for taking a drug known to influence psychomotor performance.

Each subject was given ten successive trials on tracing the zig-zag line in the mirror-blind. Immediately following these trials, the star was traced for one trial in the mirror-blind. Time, in seconds, was recorded for each trial. High scores, on both predictor and criterion, indicate inefficient performance.

Results and discussion. Table 1 presents the means and standard deviations of the spatial reversal task on the zig-zag line. It can be seen that both the mean number of seconds to complete the task and the variability are decreasing over trials. The correlations between status on the predictor trials and the criterion are also presented on Table 1. All correlations were significant ($p < .05$) except for Trial 1 ($p = .06$). The highest correlation was at Trial 4 for these status measurements.

An inspection of the intertrial correlations presented on Table 2 shows that the correlations display rough superdiagonal form (Jones, 1962). That is, as one moves down the columns of the correlations matrix or across rows to the left, the correlations increase in size. Adjacent measurements of reversal performance, then, correlate more highly than remote ones. Jones (1970b) has found this pattern to be the general rule over trials of practice, with the exception of very simple psychomotor tasks.

Table 3 presents a decomposition of the total correlation matrix of the ten predictor trials into rate and terminal process components, as suggested by Jones (1970a). Jones hypothesizes that for intertrial correlation matrices having superdiagonal form, the consistency of performance over trials is due to some combination of a rate and a terminal process. The terminal process is defined as the relative ordering of subjects when all have reached their terminal positions. The extent to which rate processes exist between trials, then, indicates the extent to which individual differences in rate of change are contributing to the consistency of performance. Jones (1970a) suggests that the rate processes are usually strongest during the early stages of practice and gradually decrease as the terminal process takes over in later stages of practice. Since true asymptote is never reached, Jones suggests that the last trial in the matrix be used to estimate terminal position.

On Table 3, the part of the intertrial correlation due to terminal position (Trial 10), appears above the diagonal, while the rate processes appear below it. It can be seen that the terminal processes are becoming stronger late in practice by the increase of correlations moving down the columns and across the rows. The rate processes, on the other hand, are strong before Trial 4, but then become small and irregular after this point. Thus, the patterns of performance indicate that there are consistent differences between subjects before Trial 4, which are independent of their terminal positions. This indicates that subjects are changing at different rates. The terminal process starts at Trial 4, but stays at a constant strength until Trial 7. At Trial 7, the terminal process begins to increase.

On Table 3, the triangles enclose what appear to be different stages for the series of trials. Moving down the main diagonal, the correlations in the first triangle on either side mark the termination of the rate process. The second set of triangles designate intermediate trials in which consistency is mainly due to terminal process, but the terminal process is not increasing with practice. The third set of triangles mark late stages of practice in which the terminal process increasingly determines consistency between trials.

It is suggested by determining where the rate process is influencing intertrial correlations, the point at which the change measure should originate can be designated. For the matrix presented on Table 3 the rate process is strong on Trial 1 and Trial 2, weakens on Trial 3 and then fades by Trial 4. Thus, initial status and origin of change would be best at Trial 1, Trial 2 or Trial 3.

To look at the relationship of modifiability to current status on this predictor, several rate scores were computed. Table 4 presents the intercorrelations of these two measures. Rate was computed by the raw gain between status at an earlier trial and a later trial. Table 4 is to be read as follows: the upper left-hand correlation, .69 is the correlation between status on Trial 1 and gain between Trial 1 and Trial 3, etc. It can be seen that the more distant the two points over which gain is computed, the higher the intercorrelations between the two. This indicates that the modifiability over practice is the least independent of initial status when there is the most intervention. That is, with large amounts of intervention, those showing the poorest initial performance change the most while this is less true with lesser degrees of intervention. Also, it should be noticed that status on Trial 1 and gain to final stages are indistinguishable on this task. This extremely high correlation to gain score and non-significant correlation to the criterion measure eliminates Trial 1 from being a starting point from which to measure change.

Table 5 presents the correlations of the gain measures to the criterion, the star. With one important series of exceptions, gain does not correlate at all with the criterion. This is analogous to Woodrow's findings that gains are not correlated with more complex ability tests. However, when Trial 4 is used as an initial status measurement, slope from this trial does correlate significantly with the criterion. That is, those who show large rates of change from Trial 4 to, later trials tend to do poorly (take a longer time) on the criterion. However, gain away from Trial 5 and other later trials again shows no correlation with the criterion. Trial 4 seems to mark a critical stage in practice, then. If an individual makes large gains after Trial 4, regardless of the route taken up to this point, then he is less likely to perform well on the criterion.

Trial 4 has been indicated as an important phase of practice by both internal and external criteria. From external criteria, prediction of a complex task, it was noted that change from Trial 4 implied poorer performance on the criterion task. From internal criteria, it was noted that Trial 4 marked the end of the rate process and the beginning of the terminal process. However, how would it be known that the critical point in prediction coincided with the beginning of the terminal process, rather than at a later stage?

Referring again to Table 3, it was noticed there was a phase between Trial 4 and Trial 8 in which there were no increments in the terminal process. Individuals were not making progress toward final ordering until late in practice at Trial 8. This indicates that there are actually two phases at which gain is important, both early and late in practice, with a series of intermediate trials not producing increasing consistency either by terminal or rate processes.

Table 6 presents the increased percentage of variance accounted for in the criterion when gain score is added to initial status in a regression equation. It can been seen that the highest increment in prediction occurs when Trial 2 is initial status and gain is computed between Trial 2 and Trial 4. The multiple R, not reported on Table 6, was .52. Also significantly increasing prediction at the .01 level is the gain between Trial 3 and Trial 4, using Trial 3 as initial status. Change between Trial 2 and Trial 3 added nothing to predictability, as would be expected since both are in the rate process phase of practice.

Change occurring late in practice, from Trial 8 and beyond, also yields significant beta weights for gain scores. It can be seen on Table 6 that all gain computed beyond Trial 8 yielded significantly increased predictability.

It is interesting to note, however, that gain from the rate process trials, Trial 2 and Trial 3, to any of the intermediate trials, Trial 5, Trial 6, Trial 7, and Trial 8, did not produce any increased predictability. However, when gain is computed to Trial 9 or Trial 10, significant beta weights for gain are seen again. Apparently what has happened is that during these intermediate trials, in which no progress is made toward terminal position, individuals changing early in practice are at a plateau while others are gaining. If status is measured at Trial 8, however, it can be seen that late change again is related to the criterion. Thus, two critical periods are noted, the termination of the rate process and approach to terminal position. In agreement with this interpretation are the significant increments to prediction yielded by the gain from Trial 5 to Trial 9 or Trial 10.

It can be seen, then, that for spatial reversal performance, prediction by the addition of gain scores is very sensitive to the stage of practice. However, in most cases a truly adequate criterion to define the appropriate stage to use will simply not be available. In fact, the more general the ability measure, the more disadvantageous it will be to depend on criterion measures. Fortunately, molar correlation analysis (Jones, 1970a) is also very sensitive to stages of practice and reflects the differential processes by which individuals arrive at their terminal positions. This method should be effective in designating optimum stages of practice or levels of intervention for more general abilities.

To explore the possibility that there may be population differences with respect to the improvement of prediction using gain scores, two groups of subjects were designated. Subjects having better predictability of criterion performance when gains were added formed one group and subjects for whom gain either made no difference or decreased predictability formed the other group. Table 7 presents the trial means and standard deviations. None of these measures, taken individually, reached the .05 level. It is concluded, then, that those who over-achieve on the basis of prediction from initial status only are equally distributed over the range of the prediction values for this task. Population differences in predictability from unexpected gains may have to be found for extrinsic factors, such as age, race, and SES, rather than individual differences intrinsic to the status measurement.

General Discussion and Conclusions

The spatial reversal data indicate that the approach suggested here to psychometrically distinguish aptitude from ability has some feasibility. The target design for this approach is a test-intervention-retest sequence. Thus, individuals will be distinguished within current status levels by the differential amount of sensitivity to a single standardized learning experience.

Cronbach & Furby (1970) consider the selection of individuals on the basis of residualized gain, as suggested here, to be unclear as to purpose. That is, it is difficult to determine if the unexpected gain was either accidental, due to underestimation by the pretest or overestimation by the post-test. Thus, it is unclear as to how these individuals should be differentially treated. However, the problem noted by Cronbach & Furby is actually an empirical question: will the use of residualized gain scores lead to increments in predictability? If the answer to this question is affirmative then it can be assumed that high unexpected gains are due to underestimation by the pretest.

Another very important issue in the use of modifiability in prediction is the question of which population will show increased predictability. This issue is complex, since the degree of intervention used may well determine which population will be selected. If sub-cultures can be said to differ with respect to how favorable the environment is to the development of a given ability, then the average points of these populations on their aptitude-ability curves will vary. One population may be at a very low point on this curve due to an extremely disadvantageous environment while the other is at a mid-range point. The difficulty is that, as previously discussed, the average rate of change between two points does not reflect whether instantaneous rate is increasing or decreasing. Thus, if a low degree of intervention is chosen, the disadvantaged population may show a slow rate of change. There would be no way of knowing if this were due to being at the end of the curve (where rate decreases) or at the beginning (where rate increases).

As shown in the spatial reversal data, there is more than one stage of practice or degree of intervention which will provide increased predictability. However, depending on how much intervention is given, populations will differ as to average unexpected gain. Thus, population differences should be evaluated during the selection of a level of intervention. The basic choice may be between the immediate end of a rate process and the approach to a strong terminal process.

In applying this aptitude-ability approach to complex tests, there are some other issues that must be resolved. One of these is the problem of the reliability of a gain score. Although classical test theory has assumed that errors of measurement are random, it is probably true that scores at the low end of the distribution are more unreliable than those at the higher end. This means, then, that gain will be directly correlated with unreliability. However, no tests known to the authors have ever been developed and scaled such that change can be reliably measured.

A second difficulty is scaling level of intervention during the evaluation of change over intervention. It is unknown, a priori, which kinds of intervention produce the largest increment in scores. A related problem is selecting a type of intervention which has generality across populations.

If the above-mentioned difficulties can be remedied, a successful psychometric distinction between aptitude and ability will have importance both theoretically and in application. Special educational resources and remedial training programs can be selectively applied to those who would profit the most.

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FOOTNOTES

1. Consider the following regression equation:

$$x_1 = \beta_2 x_2 + \beta_3 x_3$$

where 1 refers to the criterion deviation score, 2 refers to the deviation on initial status and 3 refers to deviation of the raw gain score. The beta weight for raw gain can be computed as follows:

$$\beta_3 = \frac{r_{13} - r_{12} r_{23}}{1 - r_{23}^2}$$

and the part correlation of the criterion and raw gain, removing the effects of initial status (definitionally the correlation of the residualized gain score and the criterion) is as follows:

$$r_{1(3.2)} = \frac{r_{13} - r_{12} r_{23}}{\sqrt{1 - r_{23}^2}}$$

Then

$$r_{1(3.2)} = \sqrt{1 - r_{23}^2} \quad \beta_3$$

TABLE 1

Trial Means, Standard Deviations and Correlations with Criterion

Trial	1	2	3	4	5	6	7	8	9	10
$\bar{X}$	97	61	48	47	39	35	32	31	29	26
SD	48	27	18	20	14	10	10	10	8	6
Correlation with Criterion	.23	.28*	.37**	.52**	.27*	.36**	.37**	.25*	.41**	.44**

* $p < .05$
** $p < .01$

TABLE 2

Means, Standard Deviations and Intertrial Correlations

Trial	1	2	3	4	5	6	7	8	9	10	$\bar{X}$	SD
1	---	.81	.66	.36	.38	.34	.34	.19	.23	.25	97	48
2	---	---	.72	.44	.36	.38	.41	.24	.34	.35	61	27
3	---	---	---	.60	.61	.67	.68	.53	.59	.54	48	13
4	---	---	---	---	.55	.50	.58	.60	.67	.62	47	20
5	---	---	---	---	---	.62	.69	.70	.65	.68	39	14
6	---	---	---	---	---	---	.77	.66	.64	.65	35	10
7	---	---	---	---	---	---	---	.70	.66	.66	32	10
8	---	---	---	---	---	---	---	---	.82	.76	31	10
9	---	---	---	---	---	---	---	---	---	.81	29	8
10	---	---	---	---	---	---	---	---	---	---	26	6

TABLE 3

Decomposition of the Intertrial Correlations into Rate and Terminal Process Components

Trial	1	2	3	4	5	6	7	8	9
1	---	.09	.14	.16	.17	.16	.17	.19	.20
2	.72	---	.19	.22	.24	.23	.23	.27	.28
3	.52	.50	---	.33	.37	.35	.36	.41	.44
4	.20	.22	.27	---	.42	.40	.41	.47	.50
5	.21	.12	.24	.13	---	.44	.45	.52	.55
6	.18	.15	.32	.10	.16	---	.43	.49	.53
7	.19	.18	.32	.17	.24	.34	---	.50	.53
8	.00	.01	.12	.13	.18	.17	.20	---	.62
9	.03	.06	.15	.17	.10	.11	.13	.20	---

Note:--The terminal process appears above the main diagonal; the rate process below it.

TABLE 4

Correlations of Gain Scores with Corresponding Status

Gain from Trial	Gain to Trial									
	1	2	3	4	5	6	7	8	9	10
1	---	.85	.94	.91	.96	.93	.98	.98	.99	.99
2	---	---	.76	.71	.86	.93	.92	.93	.96	.97
3	---	---	---	.32	.62	.82	.80	.82	.90	.94
4	---	---	---	---	.72	.86	.85	.87	.93	.96
5	---	---	---	---	---	.71	.67	.70	.83	.91
6	---	---	---	---	---	---	.28	.42	.64	.78
7	---	---	---	---	---	---	---	.43	.67	.81
8	---	---	---	---	---	---	---	---	.63	.44
9	---	---	---	---	---	---	---	---	---	.61

TABLE 5

Correlations of Gain Scores with Criterion

Gain from Trial	Gain to Trial									
	1	2	3	4	5	6	7	8	9	10
1	---	.11	.12	.01	.16	.16	.15	.18	.17	.18
2	---	---	.06	-.11	.15	.16	.15	.20	.17	.19
3	---	---	---	-.24	.18	.21	.19	.27	.23	.24
4	---	---	---	---	.39**	.39**	.40**	.49**	.45**	.45**
5	---	---	---	---	---	.01	-.01	.13	.05	.09
6	---	---	---	---	---	---	-.04	.14	.05	.12
7	---	---	---	---	---	---	---	.18	.09	.15
8	---	---	---	---	---	---	---	---	-.15	-.04
9	---	---	---	---	---	---	---	---	---	.10

** $p < .01$

TABLE 6

Change in Percentage of Variance Accounted for by the Addition of Gain Scores in Regression Equations

Gain from Trial	Gain to Trial								
	2	3	4	5	6	7	8	9	10
2	---	.06	.19**	.03	.07	.08	.03	.11*	.13*
3	---	---	.14**	.00	.02	.03	.00	.05	.08*
4	---	---	---	.00	.01	.01	.01	.01	.02
5	---	---	---	---	.06	.07	.01	.09*	.12*
6	---	---	---	---	---	.02	.00	.05	.07
7	---	---	---	---	---	---	.00	.05	.07
8	---	---	---	---	---	---	---	.13*	.15**
9	---	---	---	---	---	---	---	---	.19**

* $p < .05$
** $p < .01$

TABLE 7

Comparison of Performance between Subjects with Improved and Unimproved Predictability Using Modifiability

Trial	Subjects with Improved Predictability N = 27		Subjects with Unimproved Predictability N = 18	
	$\bar{X}$	SD	$\bar{X}$	SD
1	93.11	47.12	102.33	50.37
2	61.33	29.84	60.22	23.24
3	48.33	19.60	47.39	14.56
4	45.33	21.93	48.50	17.63
5	39.22	14.65	38.06	13.93
6	33.60	10.08	36.44	10.27
7	31.37	11.76	32.78	8.86
8	29.82	8.74	32.28	12.14
9	29.48	8.99	27.67	6.17
10	25.59	6.78	26.39	5.68
Criterion	101.74	60.75	106.39	40.07

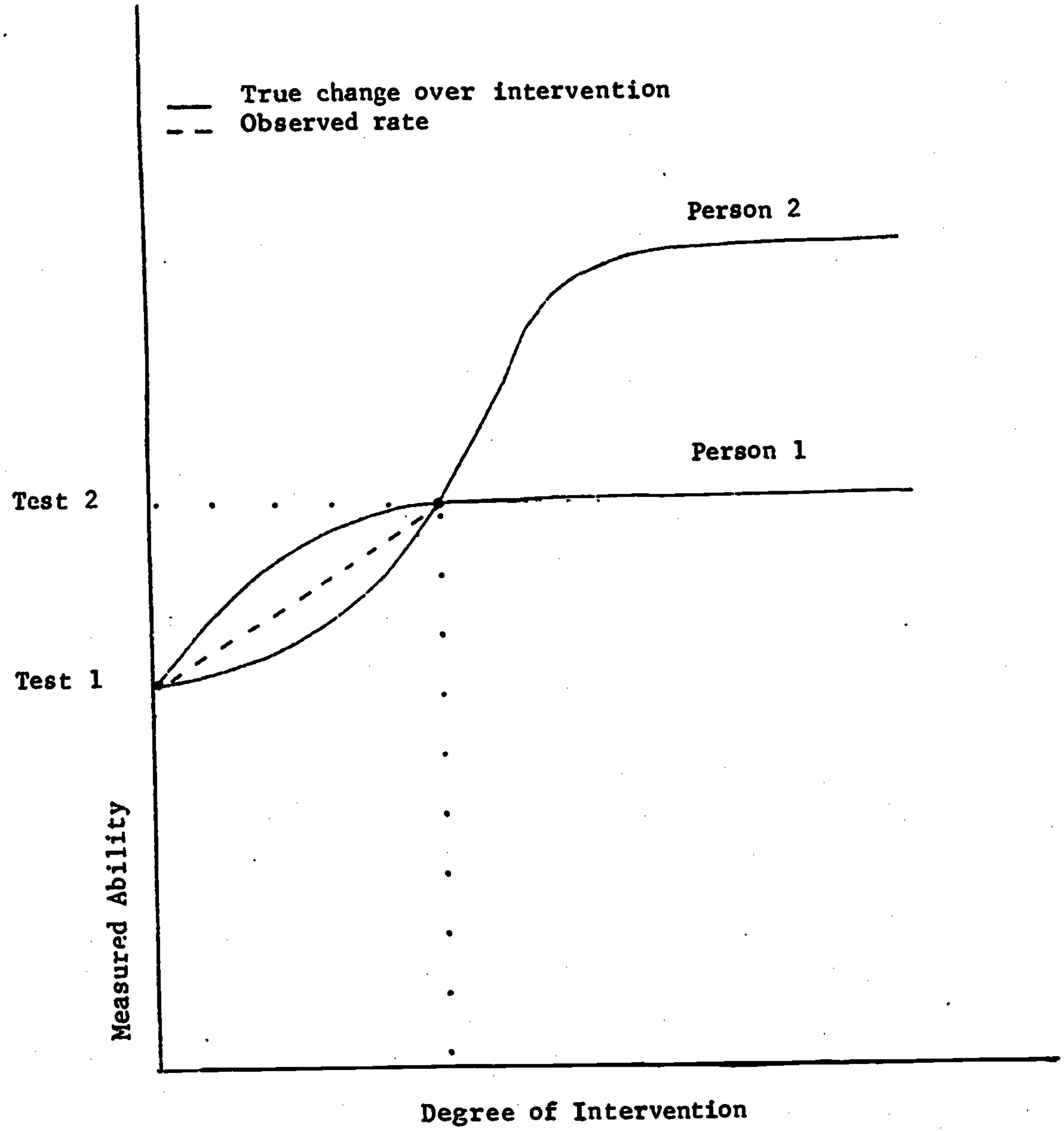

Fig. 1. Hypothetical ability curves and observed rate for two individuals.

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