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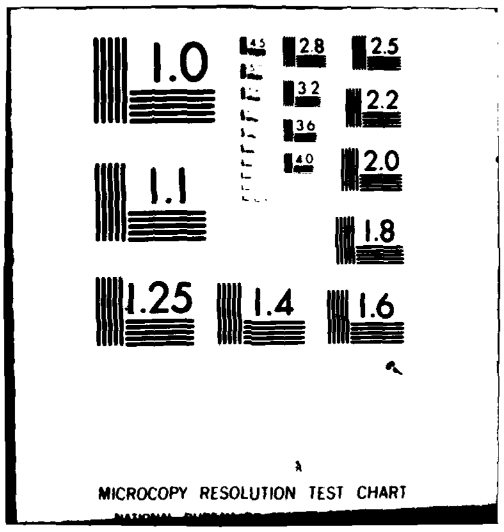

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IMPLICATIONS OF REALISTIC UTILITY FUNCTIONS FOR PLACEMENT USING APTITUDE-TREATMENT INTERACTION

D. R. DIVGI
UNIVERSITY OF IOWA

REPORT PREPARED UNDER OFFICE OF NAVAL RESEARCH
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MELVIN R. NOVICK, PRINCIPAL INVESTIGATOR
UNIVERSITY OF IOWA
IOWA CITY, IOWA

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When aptitude-treatment interaction (ATI) is used in placement decisions, it is generally assumed that a candidate should be placed in the treatment whose regression equation yields a higher predicted score. This can be justified using decision theory if utility functions are assumed linear and hence, unbounded. However, realistic utility functions ought to be bounded. Then the conventional placement rule is invalid. The optimum decisions depend on both the prediction equations and the utility functions. Therefore, the decision

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Implications of Realistic Utility Functions for Placement Using Aptitude-Treatment Interaction

D. R. Divgi
University of Iowa

Abstract

When aptitude-treatment interaction (ATI) is used in placement decisions, it is generally assumed that a candidate should be placed in the treatment whose regression equation yields a higher predicted score. This can be justified using decision theory if utility functions are assumed linear and hence, unbounded. However, realistic utility functions ought to be bounded. Then the conventional placement rule is generally invalid. The optimum decisions depend on both the prediction equations and the utility functions. Therefore, the decision rule takes different forms in different situations. This is illustrated by assuming utilities to be proportional to normal distribution functions.

When two or more "treatments" or training programs are available, one would like to place each candidate in that treatment which is likely to provide the most benefit for him/her. Three kinds of information are generally involved in such decisions--information about the candidate, about the treatments, and the utilities of possible outcomes. All candidates take a test measuring their aptitude for the training they are to receive. The outcome of training is measured with an achievement test. Available knowledge about the effect of a treatment is represented by a regression equation which predicts the achievement score from the aptitude score. Aptitude-treatment interaction (ATI) is said to be present if regression equations for the various treatments differ appreciably from one to another. Utility is a monotonic non-decreasing function of the achievement score, one for each treatment.

The importance of the utility function has received scant attention in the literature. It is often said that, of two treatments, the candidate should be placed in the one which yields a higher predicted score (e.g. Cooley & Lohnes, 1976, p. 74). When the concept of utility has been included in the analysis, the utility function has generally been assumed to be linear. Cronbach and Gleser (1965, p. 310) state this assumption explicitly. Cronbach and Snow (1977, p. 41) assume that utility and aptitude have a bivariate normal distribution. Since the usual regression model assumes the criterion and predictor to be bivariate normal, this implies that utility is a linear function of the achievement score.

As pointed out by Novick and Lindley (1978, p. 183), it is not realistic to assume that utility can increase or decrease without bound. This is particularly so when the purpose of the training is to enable students to pass a particular examination. It is then more reasonable to assume that utility is some function of the probability of passing, which is a bounded function of true score. Even in other contexts, one ought to take account of the fact that success in any enterprise depends on a number of different abilities, and therefore, no single score, however high, can have infinite value.

Consider two treatments A and B, with costs per person C_A and C_B. Let utility of extremely low scores be zero, and that of extremely high scores U_A and U_B in the two treatments. We shall see later that some conclusions depend only on these maximum values, irrespective of how utility varies with the achievement score. Hence, it is convenient to write the utility functions in a manner which clearly separates their limiting values and their functional forms. Let the utility of an achievement score Y be $U_A f_A(Y)$ at the end of treatment A, and $U_B f_B(Y)$ after treatment B. Both f_A and f_B are monotonic non-decreasing with range (0,1). The value of a skill depends on its future use, not on how it was acquired. Therefore, it is reasonable to assume that $U_A = U_B$ and $f_A \equiv f_B$ in which case the utility functions are identical. However, the decision-maker may feel that training improves not only academic achievement but also other qualities such as study habits. These additional benefits, and hence the utility function, may differ from one treatment to another. We shall call the functions "similar" if $f_A \equiv f_B$ but $U_A \neq U_B$. Without loss of generality, we assume $C_A \geq C_B$. $(U_A - U_B)$ is the difference between maximum utilities. As the costlier treatment is not worth consideration unless it provides some extra benefit, we assume $U_A \geq U_B$.

We assume a normal model to predict achievement scores after treatment from aptitude scores. If the aptitude score is X, the distribution of Y after treatment A is normal with mean $\alpha_A + \beta_A X$ and variance $\sigma_A{}^2$. The corresponding regression parameters for treatment B are α_B, β_B, and $\sigma_B{}^2$. The two predicted distributions are used to calculate expected payoffs and the candidate is placed in the treatment which yields a higher value. Let the difference between expected payoffs be

$$\begin{aligned}\Delta P(x) &= -C_A + U_A E[f_A(Y)|x) + C_B - U_B E[f_B(Y)|x].\\ &= U_A E[f_A(Y)|x] - U_B E[f_B(Y)|x] - [C_A - C_B]\end{aligned}$$

The preferred placement is in treatment A if $\Delta P(x)$ is positive and in B if it is negative.

The simple assumption of bounded utility functions has important consequences. $\Delta P(-\infty) = C_B - C_A$. Therefore, for persons with very low aptitude, the recommended placement is in the less expensive treatment which is B. Similarly, for a very high test score, ΔP approaches

$$\Delta P(\infty) = (U_A - U_B) - (C_A - C_B).$$

Therefore, if $U_A - U_B < C_A - C_B$, treatment B is preferable at very high aptitudes also. In particular, the inequality will hold if achievement score is the only outcome of interest and therefore $U_A = U_B$. Then candidates with very high and very low aptitudes are placed in the same treatment irrespective of the regression slopes. This is contrary to what is usually taken for granted--that the treatment with higher slope is preferable at high aptitude and the other treatment at low aptitude. The more expensive treatment A is preferable at very high aptitude only if it provides enough additional benefits to make $U_A > U_B + (C_A - C_B)$, i.e., large enough to offset the additional cost.

In *order to study* $\Delta P(x)$ *at finite values of* X, *we now assume* that f_A and f_B are cumulative probability functions of normal distributions $N(\mu_A, \tau_A)$ and $N(\mu_B, \tau_B)$ respectively (Novick & Lindley, 1978). The use of a normal distribution function, combined with a normal regression model, yields a simple expression for expected values:

$$E[f_A(Y)|X = x) = \phi[(\alpha_A + \beta_A x - \mu_A)/ (\sigma_A^2 + \tau_A^2)^{1/2}]$$

where ϕ is the standard normal cumulative distribution function (op. cit., eqn. 2). Therefore, the condition for treatment A to be preferable can be written in terms of expected utilities:

$$\Delta U(x) = U_A\ \phi(a + bz) - U_B\ \phi(z) > C_A - C_B \tag{1a}$$

where

$$z = (\alpha_B + \beta_B\ x - \mu_B)/(\sigma_B^2 + \tau_B^2)^{1/2}, \tag{1b}$$

$$a = [(\alpha_A - \mu_A) - \beta_A(\alpha_B - \mu_B)/\beta_B]/ (\sigma_A^2 + \tau_A^2)^{1/2}, \tag{1c}$$

$$b = (\beta_A/\beta_B)\ [(\sigma_B^2 + \tau_B^2) / (\sigma_A^2 + \tau_A^2)]^{1/2}. \tag{1d}$$

The regions where one treatment is preferable to the other are separated by points where $\Delta U(x) = C_A - C_B$. The existence and locations of these points depend on four parameters. Of these, $U_A/\ U_B$ and $(C_A - C_B)/\ U_B$ depend only on costs and on maximum utilties; a and b represent the combined effects of regression equations and utility functions. The function $\Delta U(x)$ can take different forms depending on the values of these parameters. Locations of its stationary points are the solutions (if any) of

$$(2\pi)^{\frac{1}{2}}\ d\Delta U/dz = bU_A\ \exp[-(a + bz)^2/2] - U_B\ \exp[-z^2/2] = 0$$

which is written more conveniently as

$$z^2(b^2 - 1) + 2abz + a^2 - 2\ \log\ (bU_A/U_B) = 0\ . \tag{2}$$

$$\begin{aligned}
&(2\pi)^{\frac{1}{2}}\ d^2\Delta U/dz^2 \\
&= -b^2U_A(a + bz)\ \exp[-(a + bz)^2/2] + U_B\ z\ \exp\ [-z^2/2] \\
&= U_B\ \exp(-z^2/2)[(1 - b^2)z - ab]\ \text{at stationary points.}
\end{aligned} \tag{3}$$

We can classify the various possible situations according to the number of stationary points of $\Delta U(x)$.

1. $\Delta U(x)$ increases monotonically if $a = 0$, $b = 1$. This is an uninteresting case. It will occur if the two treatments have similar utility functions and identical regression equations, or a highly coincidental combination of parameters.

   Another possibility is that solutions of Eqn.(2) are complex, i.e., that

$$a^2 < 2(1 - b^2)\ \log(bU_A/U_B). \tag{4}$$

The dotted curve in Figure 1 shows an example, with $a = 0$, $b = .9$ and $U_A/U_B = 1.3$. If the difference between maximum utilities exceeds the difference between costs, i.e. $U_A - U_B > C_A - C_B$, there is a cut off score x^*. As in the conventional placement rule, treatment A is preferable if $x > x^*$ and B if $x < x^*$. However, it is interesting to note the conditions under which this occurs. Since $U_A \geq U_B + (C_A - C_B) > U_B$, inequality (4) can be satisfied only if $b < 1$. From eqn. (1d) it is clear that the condition $b < 1$ requires β_A to be not too large; in fact, if we assume similar utility functions ($\tau_A = \tau_B$) and equal residual variances, it requires that slope β_A should be <u>smaller</u> than β_B. This is contrary to the conventional rule that the treatment with steeper regression is preferable at high aptitude.

The two solutions of eqn.(2) are identical if the two sides of (4) happen to be equal. A little algebra shows that the solution is a point of inflexion, and hence $\Delta U(x)$ is monotonic non-decreasing.

2. Equation (2) becomes linear if $b = 1$ as, for example, when utility functions are similar and the regression equations differ only in their intercepts. Equation (3) shows that the stationary point is a maximum if $a > 0$ and a minimum if $a < 0$. The dashed curve in Figure 1 shows an example with $a = 1$ and $U_A/ U_B = 1.3$. If $C_A - C_B$ exceeds $U_A - U_B$ but is smaller than the maximum, treatment A is preferable in the

middle of the aptitude range while B is preferable at both very low and very high aptitudes. If $U_A - U_B > C_A - C_B$, there is a cut off score above which treatment A is preferable. The point to note is that the preferred treatment can depend on the aptitude score even when there is no aptitude-treatment interaction.

3. When eqn. (2) has two real and distinct solutions, $\Delta U(x)$ has a maximum and a minimum. This is illustrated by the solid curve in Figure 1 ($a = 0$, $b = 2$, $U_A/U_B = 1.3$). A similar curve will be obtained whenever utility functions are identical and regression for the more expensive treatment explains a larger proportion of the variance. With other values of the parameters, one or both of the extrema may lie between the asymptotes. Thus, the placement rule is highly sensitive to the parameters of the regression equations and the utility functions.

In summary, the usual placement rule (e.g. Cooley & Lohnes, 1976, p. 74) becomes invalid as soon as one makes two simple and realistic assumptions--the costs of the two treatments are unequal and the utility functions are bounded. Although the curves in Figure 1 were drawn using utility functions proportional to normal distribution functions (Novick & Lindley, 1978), it is unlikely that qualitatively different conclusions will be obtained with other functions. Placement rules based on ATI can be quite complicated, and depend not only on the regression equations (including residual variances), but also on costs and utility functions. An even more important consideration is whether differential placement is worthwhile at all. According to Cronbach and Snow (1977, p. 42), "It is the expected benefit to the extreme cases that justifies the practice of placement" (italics in the original). It is precisely the extreme cases that are most affected by assuming utilities to be bounded rather than linear. With linear utilities and ATI, the difference between utilities expected from the two treatments increases with x without bound, which is why extreme cases are important. With bounded utilities, however, the difference has limits 0 and $U_A - U_B$ at low and high aptitudes. Then it becomes possible that it is better to use the less expensive treatment for everybody. While the theoretical importance of ATI is beyond question, its usefulness for placement cannot be judged until costs and benefits of the treatments are carefully quantified.

It should be noted that the treatment given here assumes a linear regression model with homoscedastic errors. Such a model implicitly assumes that the criterion variable can take any value from $-\infty$ to ∞. (This assumption is explicit when bivariate normality is assumed.) In such a case, boundedness of the utility function implies nonlinearity with vanishing slopes as $y \to \pm\infty$. Real-life variables, on the other hand, are always finite, and therefore any nonsingular utility function is bounded. Hence the requirement of "realism" does not impose any new restrictions, and it remains quite possible that the conventional placement rule is valid. A proper treatment of this question is complicated. Floor and ceiling effects are likely to make the regression nonlinear, and error distributions heteroscedastic and skewed. Such complications are beyond the scope of this paper.

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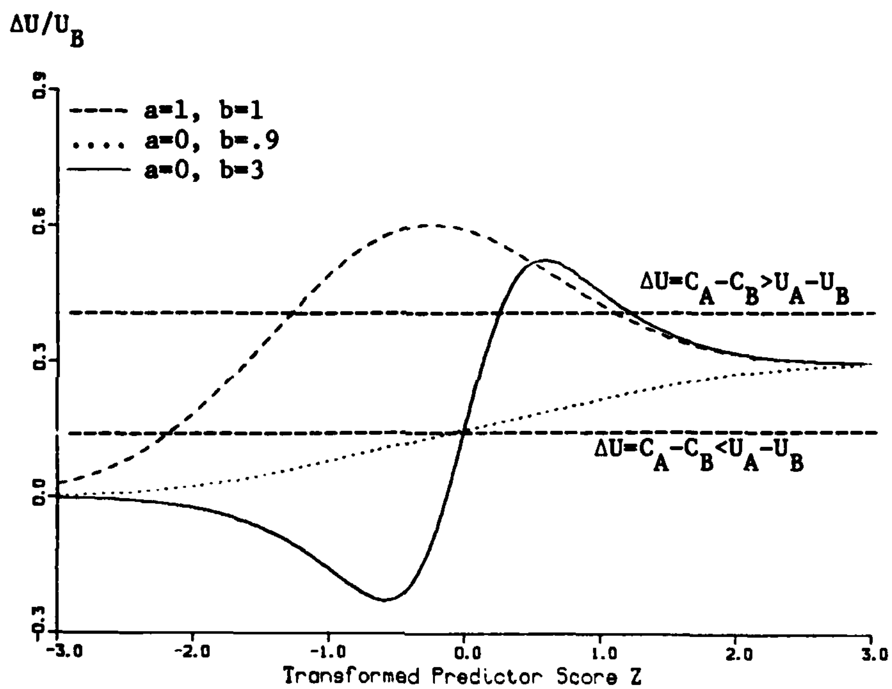
Figure 1

Possible Forms of $\Delta U(X)$ as a Function of Transformed Score Z ($U_A = 1.3\ U_B$)



Navy

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Navy Personnel R&D Center
San Diego, CA 92152

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San Diego, CA 92152

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University of California at San Diego
La Jolla, CA 92093

Navy

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ONR Branch Office
Bldg 114, Section D
666 Summer Street
Boston, MA 02210

1 Psychologist
ONR Branch Office
536 S. Clark Street
Chicago, IL 60605

1 Office of Naval Research
Code 437
800 N. Quincy SStreet
Arlington, VA 22217

5 Personnel & Training Research Programs
(Code 458)
Office of Naval Research
Arlington, VA 22217

1 Psychologist
ONR Branch Office
1030 East Green Street
Pasadena, CA 91101

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Research Development & Studies Branch
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Washington, DC 20350

1 LT Frank C. Petho, MSC, USN (Ph.D)
Code L51
Naval Aerospace Medical Research Laborat
Pensacola, FL 32508

1 Mr. Arnold Rubenstein
Naval Personnel Support Technology
Naval Material Command (08T244)
Room 1044, Crystal Plaza #5
2221 Jefferson Davis Highway
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Navy

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OP-987H
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1 Dr. Alfred F. Smode
Training Analysis & Evaluation Group
(TAEG)
Dept. of the Navy
Orlando, FL 32813

1 Dr. Richard Sorensen
Navy Personnel R&D Center
San Diego, CA 92152

1 W. Gary Thomson
Naval Ocean Systems Center
Code 7132
San Diego, CA 92152

1 Dr. Ronald Weitzman
Code 54 WZ
Department of Administrative Sciences
U. S. Naval Postgraduate School
Monterey, CA 93940

1 DR. MARTIN F. WISKOFF
NAVY PERSONNEL R& D CENTER
SAN DIEGO, CA 92152

Army

1 Technical Director
U. S. Army Research Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 HQ USAREUE & 7th Army
ODCSOPS
USAAREUE Director of GED
APO New York 09403

1 DR. RALPH DUSEK
U.S. ARMY RESEARCH INSTITUTE
5001 EISENHOWER AVENUE
ALEXANDRIA, VA 22333

1 Dr. Myron Fischl
U.S. Army Research Institute for the
Social and Behavioral Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Harold F. O'Neil, Jr.
Attn: PERI-OK
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Mr. Robert Ross
U.S. Army Research Institute for the
Social and Behavioral Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Robert Sasmor
U. S. Army Research Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Commandant
US Army Institute of Administration
Attn: Dr. Sherrill
FT Benjamin Harrison, IN 46256

1 Dr. Frederick Steinheiser
U. S. Army Reserch Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Army

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U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

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Brooks AFB, TX 78235

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Program Manager
Life Sciences Directorate
AFOSR
Bolling AFB, DC 20332

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Wright -Patterson AFB
Ohio 45433

1 Research and Measurment Division
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AFHRL/MP
Brooks AFB, TX 78235

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Technical Director
AFHRL(OT)
Williams AFB, AZ 58224

1 Jack A. Thorp, Maj., USAF
Life Sciences Directorate
AFOSR
Bolling AFB, DC 20332

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1 H. William Greenup
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Education Center, MCDEC
Quantico, VA 22134

1 Director, Office of Manpower Utilization
HQ, Marine Corps (MPU)
BCB, Bldg. 2009
Quantico, VA 22134

1 DR. A.L. SLAFKOSKY
SCIENTIFIC ADVISOR (CODE RD-1)
HQ, U.S. MARINE CORPS
WASHINGTON, DC 20380

Coast Guard

1 Mr. Thomas A. Warm
U. S. Coast Guard Institute
P. O. Substation 18
Oklahoma City, OK 73169

Other DoD

12 Defense Technical Information Center
Cameron Station, Bldg 5
Alexandria, VA 22314
Attn: TC

1 Dr. Dexter Fletcher
ADVANCED RESEARCH PROJECTS AGENCY
1400 WILSON BLVD.
ARLINGTON, VA 22209

1 Dr. William Graham
Testing Directorate
MEPCOM/MEPCT-P
Ft. Sheridan, IL 60037

1 Military Assistant for Training and Personnel Technology
Office of the Under Secretary of Defense for Research & Engineering
Room 3D129, The Pentagon
Washington, DC 20301

1 MAJOR Wayne Sellman, USAF
Office of the Assistant Secretary of Defense (MRA&L)
3B930 The Pentagon
Washington, DC 20301

1 HEAD, SECTION ON MEDICAL EDUCATION
UNIFORMED SERVICES UNIV. OF THE HEALTH SCIENCES
6917 ARLINGTON ROAD
BETHESDA, MD 20014

Civil Govt

1 Dr. Susan Chipman
Learning and Development
National Institute of Education
1200 19th Street NW
Washington, DC 20208

1 Dr. Joseph I. Lipson
SEDR W-638
National Science Foundation
Washington, DC 20550

1 Dr. John Mays
National Institute of Education
1200 19th Street NW
Washington, DC 20208

1 Dr. Arthur Melmed
National Intitute of Education
1200 19th Street NW
Washington, DC 20208

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Science Education Dev.
and Research
National Science Foundation
Washington, DC 20550

1 Personnel R&D Center
Office of Personnel Managment
1900 E Street NW
Washington, DC 20415

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Personnel R&D Center
Office of Personnel Management
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U. S. Office of Education
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Memory & Cognitive Processes
National Science Foundation
Washington, DC 20550

Non Govt

1 Dr. Erling B. Andersen
Department of Statistics
Studiestraede 6
1455 Copenhagen
DENMARK

1 1 psychological research unit
Dept. of Defense (Army Office)
Campbell Park Offices
Canberra ACT 2600, Australia

1 Dr. Isaac Bejar
Educational Testing Service
Princeton, NJ 08450

1 Dr. Werner Birke
DezWPs im Streitkraefteamt
Postfach 20 50 03
D-5300 Bonn 2
WEST GERMANY

1 Dr. Nicholas A. Bond
Dept. of Psychology
Sacramento State College
600 Jay Street
Sacramento, CA 95319

1 Dr. David G. Bowers
Institute for Social Research
University of Michigan
P. O. Box 1248
Ann Arbor, MI 48106

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1 Dr. William E. Coffman
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334 Lindquist Center
University of Iowa
Iowa City, IA 52242

1 Dr. Meredith P. Crawford
American Psychological Association
1200 17th Street, N.W.
Washington, DC 20036

1 Dr. Hans Crombag
Education Research Center
University of Leyden
Boerhaavelaan 2
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OTTAWA, CANADA K1A 0K2

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1 Dr. Leonard Feldt
Lindquist Center for Measurment
University of Iowa
Iowa City, IA 52242

1 Dr. Richard L. Ferguson
The American College Testing Program
P.O. Box 168
Iowa City, IA 52240

1 Dr. Victor Fields
Dept. of Psychology
Montgomery College
Rockville, MD 20850

1 Univ. Prof. Dr. Gerhard Fischer
Liebiggasse 5/3
A 1010 Vienna
AUSTRIA

1 Professor Donald Fitzgerald
University of New England
Armidale, New South Wales 2351
AUSTRALIA

1 Dr. Edwin A. Fleishman
Advanced Research Resources Organ.
Suite 900
4330 East West Highway
Washington, DC 20014

1 Dr. John R. Frederiksen
Bolt Beranek & Newman
50 Moulton Street
Cambridge, MA 02138

1 DR. ROBERT GLASER
LRDC
UNIVERSITY OF PITTSBURGH
3939 O'HARA STREET
PITTSBURGH, PA 15213

1 Dr. Ron Hambleton
School of Education
University of Massachusetts
Amherst, MA 01002

Non Govt

1 Dr. Chester Harris
School of Education
University of California
Santa Barbara, CA 93106

1 Dr. Lloyd Humphreys
Department of Psychology
University of Illinois
Champaign, IL 61820

1 Library
HumRRO/Western Division
27857 Berwick Drive
Carmel, CA 93921

1 Dr. Steven Hunka
Department of Education
University of Alberta
Edmonton, Alberta
CANADA

1 Dr. Earl Hunt
Dept. of Psychology
University of Washington
Seattle, WA 98105

1 Dr. Huynh Huynh
College of Education
University of South Carolina
Columbia, SC 29208

1 Dr. Douglas H. Jones
Rm T-255
Educational Testing Service
Princeton, NJ 08450

1 Professor John A. Keats
University of Newcastle
AUSTRALIA 2308

1 Dr. Mazie Knerr
Litton-Mellonics
Box 1286
Springfield, VA 22151

1 Mr. Marlin Kroger
1117 Via Goleta
Palos Verdes Estates, CA 90274

Non Govt

1 Dr. Michael Levine
Department of Educational Psychology
210 Education Bldg.
University of Illinois
Champaign, IL 61801

1 Dr. Charles Lewis
Faculteit Sociale Wetenschappen
Rijksuniversiteit Groningen
Oude Boteringestraat
Groningen
NETHERLANDS

1 Dr. Robert Linn
College of Education
University of Illinois
Urbana, IL 61801

1 Dr. Frederick M. Lord
Educational Testing Service
Princeton, NJ 08540

1 Dr. Gary Marco
Educational Testing Service
Princeton, NJ 08450

1 Dr. Scott Maxwell
Department of Psychology
University of Houston
Houston, TX 77004

1 Dr. Samuel T. Mayo
Loyola University of Chicago
820 North Michigan Avenue
Chicago, IL 60611

1 Dr. James A. Paulson
Portland State University
P.O. Box 751
Portland, OR 97207

1 MR. LUIGI PETRULLO
2431 N. EDGEWOOD STREET
ARLINGTON, VA 22207

1 DR. DIANE M. RAMSEY-KLEE
R-K RESEARCH & SYSTEM DESIGN
3947 RIDGEMONT DRIVE
MALIBU, CA 90265

Non Govt

1 MINRAT M. L. RAUCH
P II 4
BUNDESMINISTERIUM DER VERTEIDIGUNG
POSTFACH 1328
D-53 BONN 1, GERMANY

1 Dr. Mark D. Reckase
Educational Psychology Dept.
University of Missouri-Columbia
4 Hill Hall
Columbia, MO 65211

1 Dr. Andrew M. Rose
American Institutes for Research
1055 Thomas Jefferson St. NW
Washington, DC 20007

1 Dr. Leonard L. Rosenbaum, Chairman
Department of Psychology
Montgomery College
Rockville, MD 20850

1 Dr. Ernst Z. Rothkopf
Bell Laboratories
600 Mountain Avenue
Murray Hill, NJ 07974

1 Dr. Lawrence Rudner
403 Elm Avenue
Takoma Park, MD 20012

1 Dr. J. Ryan
Department of Education
University of South Carolina
Columbia, SC 29208

1 PROF. FUMIKO SAMEJIMA
DEPT. OF PSYCHOLOGY
UNIVERSITY OF TENNESSEE
KNOXVILLE, TN 37916

1 Committee on Cognitive Research
% Dr. Lonnie R. Sherrod
Social Science Research Council
605 Third Avenue
New York, NY 10016

Non Govt

1 Dr. Kazuo Shigemasu
University of Tohoku
Department of Educational Psychology
Kawauchi, Sendai 980
JAPAN

1 Dr. Richard Snow
School of Education
Stanford University
Stanford, CA 94305

1 Dr. Robert Sternberg
Dept. of Psychology
Yale University
Box 11A, Yale Station
New Haven, CT 06520

1 DR. PATRICK SUPPES
INSTITUTE FOR MATHEMATICAL STUDIES IN THE SOCIAL SCIENCES
STANFORD UNIVERSITY
STANFORD, CA 94305

1 Dr. Hariharan Swaminathan
Laboratory of Psychometric and Evaluation Research
School of Education
University of Massachusetts
Amherst, MA 01003

1 Dr. Brad Sympson
Psychometric Research Group
Educational Testing Service
Princeton, NJ 08541

1 Dr. Kikumi Tatsuoka
Computer Based Education Research Laboratory
252 Engineering Research Laboratory
University of Illinois
Urbana, IL 61801

1 Dr. David Thissen
Department of Psychology
University of Kansas
Lawrence, KS 66044

Non Govt

1 Dr. J. Uhlaner
Perceptronics, Inc.
6271 Variel Avenue
Woodland Hills, CA 91364

1 Dr. Howard Wainer
Bureau of Social Science Research
1990 M Street, N. W.
Washington, DC 20036

1 DR. THOMAS WALLSTEN
PSYCHOMETRIC LABORATORY
DAVIE HALL 013A
UNIVERSITY OF NORTH CAROL
CHAPEL HILL, NC 27514

1 Dr. David J. Weiss
N660 Elliott Hall
University of Minnesota
75 E. River Road
Minneapolis, MN 55455

1 DR. SUSAN E. WHITELY
PSYCHOLOGY DEPARTMENT
UNIVERSITY OF KANSAS
LAWRENCE, KANSAS 66044

1 Wolfgang Wildgrube
Streitkraefteamt
Box 20 50 03
D-5300 Bonn 2
WEST GERMANY

1 Dr. J. Arthur Woodward
Department of Psychology
University of California
Los Angeles, CA 90024

1 Dr. Karl Zinn
Center for research on Learning
and Teaching
University of Michigan
Ann Arbor, MI 48104

DAT
FILM