APPLICATIONS OF REALISTIC UTILITY FUNCTIONS FOR PLACEMENT USING ETC (UI)

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

D. R. Divgi
UNIVERSITY OF IOWA

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MELVIN R. NOVICK, PRINCIPAL INVESTIGATOR
UNIVERSITY OF IOWA
IOWA CITY, IOWA

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

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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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 predic-
tion 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 $f_A = f_B$ 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 $f_A \neq f_B$ but $U_A \neq U_B$. Without loss of
generality, we assume $C_A > C_B$. $(U_A - U_B)$ is the difference between maximum utilities. As the costlier treatment is not worth consideration unless it provides some extra benefit, we assume $U_A > U_B$.

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 $\sigma^2_A$. The corresponding regression parameters for treatment $B$ are $\alpha_B$, $\beta_B$, and $\sigma^2_B$. 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

$$\Delta P(x) = -C_A + U_A E[f_A(Y) | x] + C_B - U_B E[f_B(Y) | x].$$

$$= U_A E[f_A(Y) | x] - U_B E[f_B(Y) | x] - [C_A - C_B]$$

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, $\Delta P$ 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:

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

where $\phi$ 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:

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

where

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

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

$$b = (\beta_A / \beta_B) [((\sigma_B^2 + \tau_B^2) / (\sigma_A^2 + \tau_A^2)]^{1/2} \quad (1d)$$
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 utilities; $a$ 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

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

which is written more conveniently as

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

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

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 \( a = 0, \) \( b = 0.9 \) 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 \( U_A > U_B + (C_A - C_B) > U_B, \) inequality (4) can be satisfied only if \( b < 1. \) From eqn. (1d) it is clear that the condition \( b < 1 \) requires \( \beta_A \) to be not too large; in fact, if we assume similar utility functions \( (T_A = T_B) \) and equal residual variances, it requires that slope \( \beta_A \) should be smaller than \( \beta_B. \) 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 \( DU(x) \) 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 $\infty$. (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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References


Figure 1

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

\[ \frac{\Delta U}{U_B} \]

- $a = 1, b = 1$
- $a = 0, b = 0.9$
- $a = 0, b = 3$

$\Delta U = C_A - C_B > U_A - U_B$

$\Delta U = C_A - C_B < U_A - U_B$

Transformed Predictor Score $Z$
Navy

1 Dr. Ed Aiken  
Navy Personnel R&D Center  
San Diego, CA 92152

1 Dr. Jack R. Borsting  
Provost & Academic Dean  
U.S. Naval Postgraduate School  
Monterey, CA 93940

1 Dr. Robert Breaux  
Code N-711  
NAVTRAEEQUIPCEN  
Orlando, FL 32813

1 Chief of Naval Education and Training  
Liason Office  
Air Force Human Resource Laboratory  
Flying Training Division  
WILLIAMS AFB, AZ 85224

1 Deputy Assistant Secretary of the Navy  
(Manpower)  
Office of the Assistant Secretary of the Navy (Manpower, Reserve Affairs, and Logistics)  
Washington, DC 20350

1 Dr. Richard Elster  
Department of Administrative Sciences  
Naval Postgraduate School  
Monterey, CA 93940

1 DR. PAT FEDERICO  
NAVY PERSONNEL R&D CENTER  
SAN DIEGO, CA 92152

1 Dr. Henry E. Helff  
Department of Psychology, C-009  
University of California at San Diego  
La Jolla, CA 92033

Navy

1 Dr. Patrick R. Harrison  
Psychology Course Director  
LEADERSHIP & LAW DEPT. (7b)  
DIV. OF PROFESSIONAL DEVELOPMENT  
U.S. NAVAL ACADEMY  
ANNAPOLIS, MD 21402

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Chief of Naval Technical Training  
Naval Air Station Memphis (75)  
Millington, TN 38054

1 Dr. William L. Maloy  
Principal Civilian Advisor for Education and Training  
Naval Training Command, Code 00A  
Pensacola, FL 32508

1 Dr. Kneale Marshall  
Scientific Advisor to DCNO(MPT)  
OPONIT  
Washington DC 20370

1 CAPT Richard L. Martin, USN  
Prospective Commanding Officer  
USS Carl Vinson (CVN-70)  
Newport News Shipbuilding and Drydock Co  
Newport News, VA 23607

1 Dr. James J. McFride  
Navy Personnel R&D Center  
San Diego, CA 92152

1 Dr. William H. McFarland  
Navy Personnel R&D Center  
San Diego, CA 92152

1 Ted M. J. Mellen  
Technical Information Office, Code 201  
NAVY PERSONNEL R&D CENTER  
SAN DIEGO, CA 92152

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Navy Personnel R&D Center  
San Diego, CA 92152
Naval Research Laboratory

Dr. Robert G. Smith
Office of Chief of Naval Operations
OP-987H
Washington, DC 20350

Dr. Alfred F. Smode
Training Analysis & Evaluation Group
(ATAE)
Dept. of the Navy
Orlando, FL 32813

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

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

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

Dr. Martin F. Wiskoff
NAVY PERSONNEL R&D CENTER
SAN DIEGO, CA 92152

The Office of the Chief of Naval Operations
Research Development & Studies Branch
(OP-115)
Washington, DC 20350

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

Mr. Arnold Rubenstein
Naval Personnel Support Technology
Naval Material Command (08T2414)
Room 1044, Crystal Plaza 05
2221 Jefferson Davis Highway
Arlington, VA 20360
1 Technical Director
U.S. Army Research Institute for the Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Joseph Ward
U.S. Army Research Institute
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 Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333
Air Force

1 Air Force Human Resources Lab
   AFHRL/MPD
   Brooks AFB, TX 79275

1 Air University Library
   FUL/LCF 76/443
   Maxwell AFB, AL 36112

1 Dr. Earl A. Alluisi
   HQ, AFHRL (ARDC)
   Brooks AFB, TX 79275

1 Dr. Genevieve Haddad
   Program Manager
   Life Sciences Directorate
   AFOSR
   Bolling AFB, DC 20332

1 Dr. Ross L. Morgan (AFHRL/LR)
   Wright-Patterson AFB
   OH 45432

1 Research and Measurement Division
   Research Branch, AFMC/MPCYPY
   Randolph AFB, TX 78148

1 Dr. Malcolm Bie
   AFHRL/MP
   Brooks AFB, TX 79275

1 Dr. Marty Rockway
   Technical Director
   AFHRL/BT
   Williams AFB, AZ 85224

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

Marines

1 H. William Greenup
   Education Advisor (EO31)
   Education Center, MCDEC
   Quantico, VA 22134

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

1 Dr. A. L. Slafkosky
   SCIENTIFIC ADVISOR (GD-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
Alexandria, VA 22314

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 (A&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
1 Charles Myers Library
Livingstone House
Livingstone Road
Stratford
London E15 2LJ
ENGLAND

1 Dr. Kenneth E. Clark
College of Arts & Sciences
University of Rochester
River Campus Station
Rochester, NY 14627

1 Dr. Norman Cliff
Dept. of Psychology
Univ. of Sc. California
University Park
Los Angeles, CA 90007

1 Dr. William E. Coffman
Director, Iowa Testing Programs
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
Oesperhavelaan 2
2334 EH Leyden
The NETHERLANDS

1 Dr. Emmanuel Donchin
Department of Psychology
University of Illinois
Champaign, IL 61820

1 LCOL J. C. Eggenberger
DIRECTORATE OF PERSONNEL APPLIED RESEARCH
NATIONAL DEFENCE HQ
101 COLONEL BY DRIVE
OTTAWA, CANADA K1A OK2

1 Dr. Leonard Feldt
Lindquist Center for Measurement
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
Liebigasse 5/3
A 1010 Vienna
AUSTRIA

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

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

1 Dr. John R. Frederiksen
Belt Perenek & 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 01003
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  
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Carmel, CA 93923

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  
Am T-255  
Educational Testing Service  
Princeton, NJ 08540

1 Professor John A. Keats  
University of Newcastle  
AUSTRALIA 2308

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

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

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 08540

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Dr. David Tissen
Department of Psychology
University of Kansas
Lawrence, KS 66044
Mon Govt.

1 Dr. J. Whalen
Perceptronic, Inc.
2271 Yerba Buena Avenue
Woodland Hills, CA 91364

1 Dr. Howard Weiner
Bureau of Social Science Research
1330 1st Street, N.W.
Washington, DC 20036

1 Dr. Thomas Hallsten
Psycovisual Laboratory
David Hall 017A
University of North Carolina
Chapel Hill, NC 27514

1 Dr. David J. Weiss
2500 Elliott Hall
University of Minnesota
75 T. River Road
Minneapolis, MN 55455

1 Dr. Susan E. Whiteley
Psychology Department
University of Kansas
Lawrence, Kansas 66044

1 Wolfgang Wildgrube
Streekstraat
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