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The Effect of Item Parameter Estimation Error on Decisions Made Using the Sequential Probability Ratio Test

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Judith A. Spray
Mark D. Reckase

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Judith A. Spray, Mark D. Reckase

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Judith A. Spray
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ABSTRACT

A series of computer simulations were performed in order to observe the effects of item response theory (IRT) item parameter estimation error on decisions made using an IRT-based sequential probability ratio test. Specifically, the effects of such error on misclassification rates and the average number of items required for either a mastery (pass) or nonmastery (fail) decision were observed under varied SPRT conditions. These conditions included the *a priori* or nominal type I (α) and type II (β) error rates, the simple hypotheses tested by the SPRT procedure, and the composition of the item pool (specifically the *a*, *b* and *c* parameters which characterized the items according to a three-parameter logistic IRT model) used to administer the SPRT. The results of these simulations showed that these SPRT decisions are not greatly affected by this particular level of error in parameter estimates modeled in this study. Misclassification error rates were slightly lower and average numbers of items required for a decision were slightly greater when estimation error in the item parameters was present, but such differences appear to be negligible.

The Effect of Item Parameter Estimation Error on Decisions Made Using the Sequential Probability Ratio Test

Wald's (1947) sequential probability ratio testing (SPRT) procedure has been proposed as a technique for making pass-fail or mastery-nonmastery decisions in adaptive testing situations (Reckase, 1983). The SPRT was originally proposed by Wald in order to decide between two simple hypotheses, H_0 and H_1, or

$$H_0: \theta = \theta_0$$

vs.

$$H_1: \theta = \theta_1,$$

where θ is an unknown parameter of the distribution of some random variable, $\underline{X}$. In a cognitive testing situation, the random variable, $\underline{X}$, is the response to a test item and is usually assumed to be a dichotomous response, correct or incorrect.

In the case of cognitive testing, the random variable, $\underline{X}$, is assumed to follow a binomial distribution. If $P(\theta_i)$ is the probability that examinee $\underline{i}$ will respond correctly to any item and $Q(\theta_i) = 1 - P(\theta_i)$ is the probability of an incorrect response from examinee $\underline{i}$, then (for any single item) the random variable, $\underline{X}$, represents a single Bernoulli trial and is distributed as $\text{bin}[P(\theta_i), 1]$. Then, let

$$\pi(\theta_i) = \text{Prob}\ (\underline{X} = \underline{x} | \theta = \theta_i) = P(\theta_i)^x\ Q(\theta_i)^{1-x}$$

where

$$\underline{x} = \begin{cases} 1, & \text{correct response} \\ 0, & \text{incorrect response} \end{cases} .$$

For any single item, the probability of observing $\underline{X} = \underline{x}$ under the alternative hypothesis is $\pi(\theta_1)$. Under the null hypothesis, this probability is $\pi(\theta_0)$. The functions, $\pi(\theta_1)$ and $\pi(\theta_0)$ are called likelihood functions of $\underline{x}$. A ratio of these two functions, $L(\underline{x}) = \pi(\theta_1)/\pi(\theta_0)$, is called a <u>likelihood ratio</u>.

Two error probabilities, α and β, can be defined, where

$$\text{Prob (choosing } H_1 | H_0 \text{ is true)} = \alpha$$

and

$$\text{Prob (choosing } H_0 | H_1 \text{ is true)} = \beta \ .$$

Wald (1947) defined two likelihood ratio boundaries using inequalities which involved these error probabilities. These boundaries are $\underline{A}$ and $\underline{B}$ where

$$\text{lower boundary} = B \geq \beta/(1-\alpha)$$

and

$$\text{upper boundary} = A \leq (1-\beta)/\alpha \quad .$$

According to Wald's SPRT, trials or items would be observed in sequence, $\underline{x}_1, \underline{x}_2, \ldots, \underline{x}_n$, and following each observation, the likelihood ratio, $L(\underline{x}_1, \underline{x}_2, \ldots, \underline{x}_n)$, would be computed, where

$$L(\underline{x}_1, \underline{x}_2, \ldots, \underline{x}_n) = \frac{\pi_1(\theta_1) \cdot \pi_2(\theta_1) \cdots \pi_n(\theta_1)}{\pi_1(\theta_0) \cdot \pi_2(\theta_0) \cdots \pi_n(\theta_0)} \quad .$$

The likelihood function then would be compared to the boundaries, $\underline{A}$ and $\underline{B}$. If

$$L(\underline{x}_1, \underline{x}_2, \cdots, x_n) \geq A,$$

then H_1 is accepted. If

$$L(\underline{x}_1, \underline{x}_2, \cdots, \underline{x}_n) \leq B,$$

then H_0 is accepted. If

$$B < L(\underline{x}_1, \underline{x}_2, \cdots, \underline{x}_n) < A,$$

then another trial is observed, or in the case of cognitive testing, another item is administered.

Once α, β and the hypotheses are set prior to testing, the stopping rules of the test (i.e., the boundaries) are defined. Although α and β are determined prior to observing $\underset{\sim}{x}$, where $\underset{\sim}{x}' = (\underline{x}_1\ \underline{x}_2\ \cdots\ \underline{x}_n)$, Wald (1947) pointed out that the actual error rates observed in practice, α^* and β^*, would be bounded from above by

$$\alpha^* \leq \alpha/(1-\beta)$$

and

$$\beta^* \leq \beta/(1-\alpha)$$

(see Wald, 1947, p. 46). This means that even though the nominal error probabilities, α and β, are established prior to testing, the actual error rates can be less than these nominal rates, or even greater than the nominal rates.

Reckase (1983) reported the results of computer simulation research of the SPRT procedure as it applied to tailored or computerized adaptive testing (CAT) for making mastery testing decisions. He noted that this research had three purposes: (1) to obtain information on how the SPRT procedure functioned when items were selected from the item pools on the basis of maximizing item information rather than on the basis of a simple random sampling procedure; (2) to gain experience in selecting values of θ_0 and θ_1, assumed to be the two critical values of ability required to be classified as nonmaster or master, respectively; and (3) to obtain information on the effects of guessing on the accuracy of classification when the form of $P(\theta)$ was the one-parameter logistic IRT (item response theory) model but a three-parameter logistic model was used to determine the responses.

Reckase's first concern, (I) above, was that, in a given pool of test items, only a small portion of these items would be available for selection for a given examinee and that the selection of test items would be based on estimates of θ after the administration of, say $\underline{n}$ items. This is because the selection of the $\underline{n}$+1st item is dependent upon maximum item information at $\hat{\theta}_n$, max $I(\hat{\theta})_n$, where

$$I(\hat{\theta}_n) = \frac{P'(\hat{\theta}_n)}{P(\hat{\theta}_n)Q(\hat{\theta}_n)},$$

and $P'(\hat{\theta}_n)$ is the derivative of $P(\theta)$ w.r.t. θ, evaluated at $\hat{\theta}_n$.

It would appear that this nonrandom selection process would not really be a problem because the stopping rule of the SPRT is determined by prior knowledge of α, β, θ_0 and θ_1 before the test even begins and because $L(\underline{x}, \underline{x}_2, \ldots, \underline{x}_n)$ is written as the product of the individual item likelihood ratios through the assumption of local independence of the $\underline{x}$, given θ_i.

However, a problem may occur when it is time to generalize the results of the mastery/nonmastery decision-making process, as defined by the SPRT. In most mastery situations, it is desirable to generalize the results of a mastery test to the entire domain of objectives measured by the test, and this domain is usually represented by the entire item pool. If, however, items are selected on the basis of max $I(\hat{\theta}_n)$, then inferences made to the entire pool of items may be questionable. On the other hand, one could always claim that the inferences are actually being made or generalized to the ability level or the latent trait value (call it θ_c) required before an individual examinee can pass the criterion number of items in the item pool, $\pi(\theta_c)$.

Perhaps a more serious concern is the effect of assuming that the function, $P(\theta_i)$, is only a function of θ_i, and known item parameters. For the IRT models which would be assumed to define $P(\theta_i)$ explicitly, the item parameters are usually treated as known values in CAT administrations. The item pool contains values of these item parameters so that $L(\underline{x}_1, \underline{x}_2, \ldots, \underline{x}_n)$ and $I(\hat{\theta}_n)$ can be computed during the test. However, these values are, themselves, estimates of the true but unknown item parameters. The estimates have been obtained in calibration computer runs prior to the CAT administrations and are stored along with the actual items in the pool.

The present computer simulation study was designed to investigate the effects of item parameter estimation error on the characteristics of the SPRT procedure. In this first phase of a thorough investigation, a strict SPRT was administered, meaning that the test was not adaptive (i.e., θ was not estimated and items were not selected for administration based on max $I\{\hat{\theta}\}$).
The research question to be answered by these simulations was, "What are the effects on observed type I (α^*) and type II (β^*) error rates when an SPRT is administered from item pools which contain items whose parameters are estimates rather than known values?" A secondary interest was to observe the

effects of these conditions on the average number of test items required to make a classification decision at each value of θ (particularly at θ_0 and θ_1). This number, called the average sample number (ASN) is a function of the stopping rule of the tests (i.e., it is a function of α, β, θ_0 and θ_1).

Method

Two hundred eighty-eight computer simulations were completed on either an IBM PC or XT. These 288 simulations represented one combination of conditions from a 2 X 4 X 3 X 3 X 4 completely crossed design. Each of these runs consisted of 1000 replications of an SPRT administered to all of 24 hypothetical examinees with ability, θ_i, ranging from -3.0 to +3.0, incremented by .25.

The research design conditions were (1) an estimation error condition, (2) composition of the item pools, (3) *a priori* type I error rate (α), (4) *a priori* type II error rate (β), and (5) hypotheses. It was assumed that the item pools contained items which interacted with each examinee according to a three-parameter logistic model (3-PLM) to produce a correct or incorrect response to each item.

Conditions

Estimation error. There were two levels of the estimation error condition, *absent* (*E*1) or *present* (*E*2). Under the *absent* level (*E*1), the item parameters from the items in the pools were considered to be known values, and each of the 24 hypothetical examinees in the similations with ability, θ_i, responded to the items in the pool by comparing a deviate from a uniform distribution on the open interval, 0 to 1, with the $P(\theta_i)$ function given by the 3-PLM, abbreviated as P_i.

Under the present level, it was assumed that the item parameters were actually estimates derived from previous maximum likelihood estimation (MLE) calibrations on 2500 examinees with ability, θ, distributed as normal with mean zero and variance one. According to the notation used by Thissen and Wainer (1982), the maximum likelihood estimates of the set of item parameters, ξ, are those that are located where the partial derivatives of the log of the likelihood function, summed over N examinees, are zero. If ℓ is this sum, or

$$\ell = \sum_{i=1}^{N} x \log (P_i) + (1 - x) \log (1 - P_i),$$

then, again from Thissen and Wainer (1982) but written without the i subscript, these MLEs satisfy

$$\frac{\partial \ell}{\partial \xi} = \Sigma \frac{x}{P} \frac{\partial P}{\partial \xi} - \frac{(1 - x)}{(1 - P)} \frac{\partial P}{\partial \xi} = 0 \quad . \tag{1}$$

The inverse of the negative expected value of the matrix of second derivatives of the function, ℓ, is the asymptotic variance-covariance matrix of the estimates, $\hat{\xi}$, obtained from the relationship given by (1). If the second partial derivatives of ℓ are written, in general, as $\partial^2 \ell / \partial \xi_s \partial \xi_t$, for any parameters, ξ_s and ξ_t, then

$$-E\{\partial^2 \ell / \partial \xi_s \partial \xi_t\} = N \int_{-\infty}^{\infty} \{\frac{1}{P} \frac{\partial P}{\partial \xi_s} \frac{\partial P}{\partial \xi_t} + \frac{1}{(1 - P)} \frac{\partial P}{\partial \xi_s} \frac{\partial P}{\partial \xi_t}\} \phi(\theta)\, d\theta, \tag{2}$$

where $\phi(\theta)$ is taken to be a normal density with zero mean and variance one (Thissen & Wainer, 1982). In other words, if Σ is the variance-covariance matrix of ξ, then Σ is defined by the inverse of the matrix whose elements are given by (2).

For the *present* level (*E2*) of the estimation error condition, it was assumed that the item parameters were actually estimates sampled from a multivariate normal distribution with mean vector ξ and variance-covariance matrix Σ, where ξ was given for the item pool used for a particular SPRT and Σ was computed from (2).

Item Pools. There were four types of item pools used in the simulations. The first three consisted of 500 identical items from a three-parameter logistic IRT model of the form,

$$P(\theta_i) = c + \frac{(1 - c)}{1 + \exp\{-1.7a(\theta_i - b)\}} \quad . \tag{3}$$

For the first pool (*I1*), $\underline{a} = 1$, $\underline{b} = 0$, and $\underline{c} = 0$ for all 500 items. Under the *E1* condition, these identical items represented a simple SPRT with constant success probability, $P(\theta_i)$ for a given θ_i value. Under the *E2* condition, the items were still administered in sequence but were no longer identical because each item represented a different set of item parameter estimates. For example, even though $\underline{a}_1 = \underline{a}_2 = \ldots = \underline{a}_{500}$, each $\underline{a}$ parameter represented an estimate, $\hat{\underline{a}}_j$, where

$$\hat{\underline{a}}_j = \underline{a} + \varepsilon_{\underline{a}j} ,$$

and $\varepsilon_{\underline{a}j}$ was a random deviate from a multivariate normal distribution with mean vector $\underset{\sim}{0}$ and variance-covariance matrix Σ, defined previously.

For the second item pool (*I2*), $\underline{a} = 1$, $\underline{b} = 0$, and $\underline{c} = .2$. For the third pool (*I3*), $\underline{a} = 1.5$, $\underline{b} = 0$, and $\underline{c} = .2$. Again, under *E1* these item parameters remained constant for all 500 items in a pool. However, under *E2*, item parameter values were assumed to be estimates ($\underline{a} + \varepsilon_{\underline{a}j}$, $\underline{b} + \varepsilon_{\underline{b}j}$, and $\underline{c} + \varepsilon_{\underline{c}j}$ with $\varepsilon_{\underline{a}j}$, $\varepsilon_{\underline{b}j}$, and $\varepsilon_{\underline{c}j}$ being random deviates as before).

For the fourth item pool (I4), the 500 sets of parameters were generated from a pseudo-random number generator with $a \sim U(.5, 2.5)$, $b \sim U(-3., 3.)$, and $c \sim U(.0, .2)$. This was called the random item pool.

Error Rate Conditions. Type I or α rates were .01 (A1), .05 (A2), and .10 (A3). Type II or β rates were also .01 (B1), .05 (B2), and .10 (B3).

Hypotheses. In a mastery testing situation, the usual practice is to establish a single cutoff point along the ability scale, θ_c, which corresponds to a minimum proportion of items in the domain, $\pi(\theta_c)$, that an examinee is expected to answer correctly in order to be classified as a master. The relationship between θ_c and $\pi(\theta_c)$, for example, might be

$$\frac{1}{n} \sum_{j=1}^{n} P_j(\theta_c) = \pi(\theta_c),$$

where n is the number of items in the pool representing this testing domain. Because the SPRT procedure requires the setting of two values of θ in a simple hypothesis configuration, one usually sets $\theta_0 < \theta_c < \theta_1$. The region between θ_0 and θ_1 is referred to as an indifference region. Reckase (1983) stated that "in order to use the SPRT, a region must be specified around θ_c for which it does not matter whether a pass or a fail decision is made. If high accuracy is desired for the decision rule, a narrow indifference region must be specified, but more items will be required to make the decision. As the region gets wider, the decision accuracy declines, but fewer items are required" (p. 243).

In the present study, four simple hypotheses were used to establish four sizes of indifference regions around the chosen value of $\theta_c = .00$. These sets of hypotheses (θ_0, θ_1) were (1) H1: (-.25, .25), (2) H2: (-.5, .5), (3) H3: (-.75, .75), and (4) H4: (-1.0, 1.0).

Results

The results of these 288 computer simulations focused on the effects of the E2 condition on four characteristics or measures of an SPRT: actual or observed α rate (α^*), actual or observed β rate (β^*), average sample number or ASN when $\theta = \theta_0$, and ASN when $\theta = \theta_1$. These results are given in Tables 1 through 6 in terms of overall and marginal means and standard deviations of these variables under the E1 and E2 conditions.

Actual Error Rates

Table 1 shows that even though a nominal type I error or α rate was established prior to the usual SPRT, the observed rate (α^*) was actually lower than the nominal one. Under the E1 condition, α^* was .007, .034, and .060, for A1, A2, and A3 nominal rates, respectively. Under the E2 condition, these observed α rates were lower still, .005, .030, and .065, for A1, A2, and A3. However, the overall decrease in α^* for E2 (i.e., from .036 to .033) was quite small and probably insignificant from a practical standpoint.

There was a relatively large decrease in overall mean α^* under E2 for the fourth hypothesis, H4, where the mean $\alpha^* = .027$ (see Table 1). A further analysis of α^* by the nominal error rates, A1, A2, and A3 for this E2-H4 combination revealed that all three values of α^* were lower for H4, although these values were usually lower for each hypothesis under E2, regardless of the nominal α level.

The two exceptions, as seen in Table 2, are at the A3 level. No reasons for these lower α^* were apparent from inspection of further analyses within the design.

Table 3 shows that the observed β rates (β^*) were affected even less under the E2 condition than the α^* rates. Although β^* was usually smaller under E2 versus E1, this difference was never greater than .002. However, there was a relatively large decrease in β^* under the I4 condition for both E1 and E2. Table 4 shows that the β^* rate was lower under all nominal β rates when the item pool consisted of items with variable item parameter values (either known or estimated).

Average Sample Numbers

The overall effect of E2 on average sample number (ASN) was to increase the number of test items required to make a classification decision at each θ level for which the ASN was analyzed. Table 5 shows that when $\theta = \theta_1$, this overall increase in ASN amounted to 1.1 items from E1 to E2. The greatest increase occurred under the H1 condition (42.5 to 46.8).

Table 6 shows that when $\theta = \theta_0$, the increase in ASN from E1 to E2 was even smaller (.8). Again, the greatest increase occurred under the H1 condition (41.5 to 44.2).

It was interesting to note the effects of different item pools on the ASN. Tables 5 and 6 show that, regardless of the estimation error condition, the ASN increased when items within the pool included a nonzero value for c, the pseudo-guessing parameter. When items became more discriminating (i.e., when the discrimination or a parameter changed from 1.0 to 1.5), a decrease in ASN was noted. However, when items had variable item parameters, as was the case under the I4 or random item pool condition, the ASN increased significantly. The observed effects on the ASN under the fixed item pools, I1, I2, and I3, are more easily understood when the hypotheses and the indifference regions are transformed into functions of θ_0 and θ_1, namely $\pi(\theta_0)$ and $\pi(\theta_1)$. Because all of the items in these pools are identical,

$$\pi(\theta_0) = \frac{c + (1 - c)}{1 + \exp\{-1.7a(\theta_0 - b)\}} = \pi_0$$

and

$$\pi(\theta_1) = \frac{c + (1 - c)}{1 + \exp\{-1.7a(\theta_1 - b)\}} = \pi_1 \quad .$$

Table 7 shows these transformed hypotheses and indifference region lengths in terms of $\pi(\theta_0)$ and $\pi(\theta_1)$. Wald's SPRT theory predicts that the ASN for any value of θ will increase as the size of the indifference region decreases. Therefore, it is no surprise that, of the three fixed pools, the I2 pool produced the highest ASN at θ_0 and θ_1 while I3 showed the smallest overall ASN values. For the random item pool, π_0 and π_1 in Table 7 were defined in terms of the averages, $\bar{\pi}_0$ and $\bar{\pi}_1$, across the 500 sets of item parameters in I4, or

$$\bar{\pi}_0 = \frac{1}{500} \sum_{j=1}^{500} c_j + (1 - c_j)/[1 + \exp\{-1.7a_j\ (\theta_0 - b_j)\}]$$

and

$$\bar{\pi}_1 = \frac{1}{500} \sum_{j=1}^{500} c_j + (1 - c_j)/[1 + \exp\{-1.7a_j\ (\theta_1 - b_j)\}] \quad .$$

The smaller average indifference regions encountered for I4 would appear to account for larger ASN values for I4 in Tables 5 and 6.

Other changes in ASN under the various error rate and hypothesis conditions were again predicted by Wald's SPRT theory. For example, ASN is expected to decrease as α or β increases and as the indifference region around θ_c increases. Tables 5 and 6 show that this did occur under E1 and E2.

Summary and Conclusions

Administering a test using Wald's sequential probability ratio testing procedure on item pools which contain IRT parameter estimates rather than known values did not appear to have much effect on observed mastery or nonmastery classification error rates. These observed error rates were smaller when it was assumed that the item parameters were actually MLEs based on prior calibrations involving examinees with known abilities. However, these smaller observed error rates were not appreciably different from the absent-error condition, *E1*. Observed error rates under both estimation error conditions were still smaller than the nominal rates established prior to testing and this would appear to be the most important finding regarding error rates.

It should be pointed out that the amount of error in the item parameters was based on several assumptions. First, it was assumed that, during the item calibrations, ability was known. This is rarely true because ability almost always must be estimated in practice. Estimation of ability would increase the amount of error in the item parameter estimates, thereby magnifying the effects of estimation on the SPRT results. Second, the errors were derived under the assumption of normality for the (unidimensional) ability distribution. And finally these error estimates were based on asymptotic standard error formulae and large sample sizes of items and examinees were assumed.

The estimation error condition did appear to have some effect on the observed α rate when the largest indifference region was simulated (*H4*). How important this effect is in practice remains to be seen because the simulations still produced an α^* rate less than the nominal average and because this α^* rate occurred with an indifference region (-1.0, 1.0) which may be too large to be useful in actual SPRT administrations.

One noticeable finding involving β^* was the amount of decrease in this error rate, regardless of the estimation error condition, when the nature of the item pool changed in terms of item parameters. Wald's SPRT theory makes use of the local independence assumption of IRT through the formulation of the likelihood functions under H_0 and H_1 as products of probabilities. There is nothing in the SPRT theory which requires that these probabilities be constant from item to item within the pool. And yet, from Table 3, it is obvious that when these probabilities varied considerably from item to item (I4), β^* was significantly smaller than when the items did not vary at all (I1, I2 and I3 under E1) or varied by a very small amount (I1, I2, and I3 under E2). A similar effect on α^* was not observed.

On the other hand, the ASN was much larger under the I4 item pool condition, thereby leading to the following conclusion. When items are administered via SPRT procedures and those items vary considerably in P_i for a given examinee, then the ASN will be larger and the β^* rate smaller than for SPRT item pools in which the variability of P_i is smaller.

The estimation error condition did yield higher ASN values at all true θ values, in general, but these increases did not appear to be significant with the item parameter estimation error used in these simulations. According to SPRT theory, the ASN of any SPRT will be a maximum for some θ value within the indifference region, (θ_0, θ_1). The rather large values of ASN for the H1 condition, regardless of estimation error, suggest that this hypothesis could yield ASN values greater than 50 items for some examinees with θ between -.25 and .25. Therefore, H1 may be an impractical hypothesis to consider for actual SPRT administrations due to the increased test length. Hypothesis H2 or H3 may be more reasonable in practice.

When items from item pools are chosen on some nonrandom basis (e.g., selecting items which maximize $I(\hat{\theta}_n)$ on the basis of estimates of ability, $\hat{\theta}_n$), the variability of P_i for a given examinee may be minimal, and the effects of using SPRT in a CAT situation, for example, are not expected to change the characteristics of the test from those predicted by the SPRT theory, even when item parameter estimates are used. In fact, when administered as an SPRT, the CAT may even require fewer items and yield smaller classification errors when items are selected for administration on the basis of maximum information. Therefore, a second phase of this research will examine the characteristics of an SPRT when items are administered randomly from I4 versus when the items are administered on the basis of max $I(\theta)$, with θ known. A third study will compare the results of the max $I(\theta)$ procedure of item selection versus a max $I(\hat{\theta}_n)$ procedure, where θ is unknown and must be estimated after each item is presented.

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TABLE I

Actual Alpha Rate (α^*)

	N		Estimation Error E1 Absent	Estimation Error E2 Present
Overall Mean	144		.036 (0.26)	.033 (.027)
Item Pool Means	36	I1	.034 (.026)	.031 (.027)
	36	I2	.039 (.028)	.036 (.027)
	36	I3	.033 (.026)	.033 (.028)
	36	I4	.037 (.027)	.033 (.026)
α Rate Means	48	A1 (.01)	.007 (.002)	.005 (.002)
	48	A2 (.05)	.034 (.008)	.030 (.009)
	48	A3 (.10)	.067 (.014)	.065 (.015)
β Rate Means	48	B1 (.01)	.036 (.027)	.033 (.027)
	48	B2 (.05)	.036 (.027)	.033 (.027)
	48	B3 (.10)	.036 (.026)	.034 (.027)
Hypothesis Means	36	H1 (± .25)	.039 (.028)	.037 (.029)
	36	H2 (± .50)	.039 (.027)	.038 (.027)
	36	H3 (± .75)	.032 (.025)	.032 (.027)
	36	H4 (±1.00)	.034 (.027)	.027 (.023)

Note: Standard deviations are given in parentheses in columns 6 and 8.

TABLE 2

Actual Alpha Rate (α^*) Means and Standard Deviations by Hypothesis

	N	α	Estimation Error E1 Absent		Estimation Error E2 Present	
	12	A1	.007	(.002)	.004	(.001)
H1	12	A2	.038	(.007)	.035	(.007)
	12	A3	.073	(.006)	.072	(.007)
	12	A1	.008	(.002)	.007	(.001)
H2	12	A2	.038	(.006)	.035	(.008)
	12	A3	.070	(.009)	.071	(.008)
	12	A1	.005	(.002)	.004	(.001)
H3	12	A2	.029	(.006)	.027	(.008)
	12	A3	.061	(.014)	.065	(.015)
	12	A1	.006	(.003)	.004	(.002)
H4	12	A2	.032	(.009)	.024	(.006)
	12	A3	.063	(.021)	.052	(.019)

Note: A1 = .01, A2 = .05, and A3 = .10.

TABLE 3

Actual Beta Rate (β^*)

	N			Estimation Error E1 Absent		E2 Present	
Overall Mean	144			.032	(.025)	.031	(.026)
Item Pool Means	36	I1		.036	(.027)	.035	(.027)
	36	I2		.037	(.027)	.035	(.028)
	36	I3		.032	(.025)	.033	(.028)
	36	I4		.023	(.020)	.022	(.021)
α Rate Means	48	A1	(.01)	.032	(.025)	.030	(.026)
	48	A2	(.05)	.032	(.025)	.032	(.027)
	48	A3	(.10)	.032	(.026)	.031	(.027)
β Rate Means	48	B1	(.01)	.007	(.003)	.006	(.002)
	48	B2	(.05)	.030	(.011)	.028	(.012)
	48	B3	(.10)	.060	(.019)	.060	(.021)
Hypothesis Means	36	H1	(± .25)	.041	(.027)	.039	(.030)
	36	H2	(± .50)	.036	(.028)	.034	(.026)
	36	H3	(± .75)	.027	(.022)	.027	(.023)
	36	H4	(±1.00)	.024	(.020)	.025	(.023)

Note: Standard deviations are given in parentheses in columns 6 and 8.

TABLE 4

Actual Beta Rate (β^*) Means and Standard Deviations by Item Pool

Item Pool	N	β	Estimation Error: E1 Absent		Estimation Error: E2 Present	
	12	B1	.007	(.002)	.008	(.003)
I1	12	B2	.034	(.010)	.033	(.012)
	12	B3	.066	(.016)	.066	(.018)
	12	B1	.007	(.001)	.006	(.002)
I2	12	B2	.037	(.005)	.033	(.004)
	12	B3	.069	(.014)	.066	(.022)
	12	B1	.008	(.002)	.005	(.001)
I3	12	B2	.027	(.012)	.028	(.011)
	12	B3	.061	(.016)	.066	(.014)
	12	B1	.006	(.005)	.004	(.001)
I4	12	B2	.020	(.011)	.019	(.011)
	12	B3	.043	(.019)	.043	(.019)

Note: B1 = .01, B2 = .05, and B3 = .10.

TABLE 5

ASN (H_1)

	N			Estimation Error: E1 Absent		Estimation Error: E2 Present	
Overall Mean	144			17.6	(19.6)	18.7	(20.9)
Item Pool Means	36	I1		13.5	(14.3)	13.8	(14.7)
	36	I2		16.7	(16.8)	20.0	(20.5)
	36	I3		10.2	(9.6)	10.4	(9.9)
	36	I4		30.0	(27.6)	30.5	(28.6)
α Rate Means	48	A1	(.01)	22.8	(25.4)	25.5	(27.5)
	48	A2	(.05)	16.9	(17.2)	17.1	(17.8)
	48	A3	(.60)	13.1	(13.4)	13.4	(13.8)
β Rate Means	48	B1	(.01)	18.4	(20.6)	20.0	(22.6)
	48	B2	(.05)	17.1	(19.1)	19.0	(21.7)
	48	B3	(.10)	17.3	(19.4)	17.0	(18.7)
Hypothesis Means	36	H1	(±.25)	42.5	(24.2	46.8	(24.1)
	36	H2	(±.50)	14.4	(7.2)	14.3	(7.1)
	36	H3	(±.75)	8.2	(5.I)	8.2	(4.9)
	36	H4	(±1.00)	5.3	(3.3)	5.5	(3.3)

Note: Standard deviations are given in parentheses in columns 6 and 8.

TABLE 6

ASN(H_o)

	N			Estimation Error E1 Absent		E2 Present	
Overall Mean	144			16.2	(19.1)	17.0	(19.7)
Item Pool Means	36	I1		13.6	(14.6)	13.4	(14.0)
	36	I2		16.2	(18.3)	19.3	(20.9)
	36	I3		9.4	(9.5)	9.4	(9.4)
	36	I4		25.6	(26.6)	25.9	(26.5)
α Rate Means	48	A1	(.01)	15.7	(19.1)	18.1	(21.2)
	48	A2	(.05)	17.0	(20.1)	17.0	(19.8)
	48	A3	(.10)	15.9	(18.6)	15.9	(18.3)
β Rate Means	48	B1	(.01)	21.8	(25.6)	23.2	(26.4)
	48	B2	(.05)	14.6	(15.9)	15.5	(16.2)
	48	B3	(.10)	12.2	(12.5)	12.3	(12.7)
Hypothesis Means	36	H1	(±.75	41.5	(23.3)	44.2	(22.0)
	36	H2	(±.50)	12.4	(5.5)	12.8	(5.9)
	36	H3	(±.75)	6.8	(3.1)	6.8	(3.1)
	36	H4	(±1.00)	4.2	(1.7)	4.2	(1.8)

Note: Standard deviations are given in parentheses in columns 6 and 8.

TABLE 7

Hypotheses and Indifference Regions in Terms of $\pi(\theta)$

Item Pool	Hypothesis	Cutoff Proportions π_0	Cutoff Proportions π_1	Indifference Region $(\pi_1-\pi_0)$	
	H1	.395	.605	.210	
I1	H2	.299	.701	.402	
	H3	.218	.782	.564	
	H4	.154	.846	.692	
	H1	.516	.684	.168	
I2	H2	.440	.760	.320	
	H3	.337	.863	.526	
	H4	.324	.876	.552	
	H1	.477	.723	.246	
I3	H2	.375	.825	.450	
	H3	.303	.897	.594	
	H4	.258	.942	.684	
	H1	.540	.616	.076	(.093)
I4	H2	.503	.655	.152	(.172)
	H3	.466	.692	.226	(.230)
	H4	.428	.728	.300	(.270)

Note: Standard deviations for the indifference regions in I4 are given in parentheses in column 6.

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550 Camino El Estero,
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Iowa City, IA 52243

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409 Elliott Rd.
Chapel Hill, NC 27514

Dr. Robert Carroll
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Washington, DC 20370

Mr. Raymond E. Christal
AFHRL/MOE
Brooks AFB, TX 78235

Dr. Norman Cliff
Department of Psychology
Univ. of So. California
University Park
Los Angeles, CA 90007

Director,
Manpower Support and
Readiness Program
Center for Naval Analysis
2000 North Beauregard Street
Alexandria, VA 22311

Dr. Stanley Collyer
Office of Naval Technology
Code 222
800 N. Quincy Street
Arlington, VA 22217-5000

Dr. Hans Crombag
University of Leyden
Education Research Center
Boerhaavelaan 2
2334 EN Leyden
The NETHERLANDS

Dr. Timothy Davey
Educational Testing Service
Princeton, NJ 08541

Dr. C. M. Dayton
Department of Measurement
Statistics & Evaluation
College of Education
University of Maryland
College Park, MD 20742

Dr. Ralph J. DeAyala
Measurement, Statistics,
and Evaluation
Benjamin Building
University of Maryland
College Park, MD 20742

Dr. Dattprasad Divgi
Center for Naval Analysis
4401 Ford Avenue
P.O. Box 16268
Alexandria, VA 22302-0268

Dr. Hei-Ki Dong
Bell Communications Research
6 Corporate Place
PYA-1k226
Piscataway, NJ 08854

Dr. Fritz Drasgow
University of Illinois
Department of Psychology
603 E. Daniel St.
Champaign, IL 61820

Defense Technical
Information Center
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Lindquist Center
for Measurement
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Brooks AFB, TX 78235

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Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

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252 Engineering Research
Laboratory
103 South Mathews Street
Urbana, IL 61801

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University of Kansas
Psychology Department
426 Fraser
Lawrence, KS 66045

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201 Fishburne Bldg.
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1601 W. Taylor Street
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Charles & 34th Street
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51 Gerty Drive
Champaign, IL 61820

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Research and Services
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Navy Personnel R&D Center
Code 62
San Diego, CA 92152-6800

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Educational Testing Service
Rosedale Road
Princeton, NJ 08541

Prof. Lutz F. Hornke
Institut fur Psychologie
RWTH Aachen
Jaegerstrasse 17/19
D-5100 Aachen
WEST GERMANY

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Chula Vista, CA 90010

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Department of Psychology
603 East Daniel Street
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10 Trafalgar Court
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Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

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Department of Psychology
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N.S.W. 2308
AUSTRALIA

Dr. G. Gage Kingsbury
Portland Public Schools
Research and Evaluation Department
501 North Dixon Street
P. O. Box 3107
Portland, OR 97209-3107

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University of Texas-Austin
Measurement and Evaluation
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Computer-based Education
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Navy Personnel R&D Center
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Defense Manpower Data Center
Suite 400
1600 Wilson Blvd
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University of Wisconsin
Department of Statistics
1210 West Dayton Street
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210 Education Bldg.
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Stop 31-E
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Development and Studies
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Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Jesse Orlansky
Institute for Defense Analyses
1801 N. Beauregard St.
Alexandria, VA 22311

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Army Research Institute
5001 Eisenhower Blvd.
Alexandria, VA 22333

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GED Testing Service, Suite 20
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Portland State University
P.O. Box 751
Portland, OR 97207

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ACT
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Brooks AFB, TX 78235

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HumRRO
1100 South Washington Street
Alexandria, VA 22314

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CNET-PDCD
Building 90
Great Lakes NTC, IL 60088

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Department of Education
University of South Carolina
Columbia, SC 29208

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Department of Psychology
University of Tennessee
3108 AustinPeay Bldg.
Knoxville, TN 37916-0900

Mr. Drew Sands
NPRDC Code 62
San Diego, CA 92152-6800

Lowell Schoer
Psychological & Quantitative
Foundations
College of Education
University of Iowa
Iowa City, IA 52242

Dr. Mary Schratz
Navy Personnel R&D Center
San Diego, CA 92152-6800

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Navy Personnel R&D Center
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Dr. W. Steve Sellman
OASD(MRA&L)
2B269 The Pentagon
Washington, DC 20301

Dr. Kazuo Shigemasu
7-9-24 Kugenuma-Kaigan
Fujusawa 251
JAPAN

Dr. William Sims
Center for Naval Analysis
4401 Ford Avenue
P.O. Box 16268
Alexandria, VA 22302-0268

Dr. H. Wallace Sinaiko
Manpower Research
and Advisory Services
Smithsonian Institution
801 North Pitt Street
Alexandria, VA 22314

Dr. Richard E. Snow
Department of Psychology
Stanford University
Stanford, CA 94306

Dr. Richard Sorensen
Navy Personnel R&D Center
San Diego, CA 92152-6800

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University of Missouri
Department of Statistics
Columbia, MO 65201

Dr. Judy Spray
ACT
P.O. Box 168
Iowa City, IA 52243

Dr. Martha Stocking
Educational Testing Service
Princeton, NJ 08541

Dr. Peter Stoloff
Center for Naval Analysis
200 North Beauregard Street
Alexandria, VA 22311

Dr. William Stout
University of Illinois
Department of Statistics
101 Illini Hall
725 South Wright St.
Champaign, IL 61820

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

Mr. Brad Sympson
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. John Tangney
AFOSR/NL
Bolling AFB, DC 20332

Dr. Kikumi Tatsuoka
CERL
252 Engineering Research
Laboratory
Urbana, IL 61801

Dr. Maurice Tatsuoka
220 Education Bldg
1310 S. Sixth St.
Champaign, IL 61820

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Department of Psychology
University of Kansas
Lawrence, KS 66044

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University of Illinois
Educational Psychology
Champaign, IL 61820

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University of Missouri
Department of Statistics
222 Math. Sciences Bldg.
Columbia, MO 65211

Dr. Ledyard Tucker
University of Illinois
Department of Psychology
603 E. Daniel Street
Champaign, IL 61820

Dr. Vern W. Urry
Personnel R&D Center
Office of Personnel Management
1900 E. Street, NW
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Assessment Systems Corp.
2233 University Avenue
Suite 310
St. Paul, MN 55114

Dr. Frank Vicino
Navy Personnel R&D Center
San Diego, CA 92152-6800

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Division of Psychological Studies
Educational Testing Service
Princeton, NJ 08541

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Lindquist Center
for Measurement
University of Iowa
Iowa City, IA 52242

Dr. Thomas A. Warm
Coast Guard Institute
P. O. Substation 18
Oklahoma City, OK 73169

Dr. Brian Waters
Program Manager
Manpower Analysis Program
HumRRO
1100 S. Washington St.
Alexandria, VA 22314

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

Dr. Ronald A. Weitzman
NPS, Code 54Wz
Monterey, CA 92152-6800

Major John Welsh
AFHRL/MOAN
Brooks AFB, TX 78223

Dr. Douglas Wetzel
Code 12
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Rand R. Wilcox
University of Southern
California
Department of Psychology
Los Angeles, CA 90007

German Military Representative
ATTN: Wolfgang Wildegrube
Streitkraefteamt
D-5300 Bonn 2
4000 Brandywine Street, NW
Washington, DC 20016

Dr. Bruce Williams
Department of Educational
Psychology
University of Illinois
Urbana, IL 61801

Dr. Hilda Wing
NRC GF-176
2101 Constitution Ave
Washington, DC 20418

Dr. Martin F. Wiskoff
Navy Personnel R & D Center
San Diego, CA 92152-6800

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Navy Personnel R&D Center
San Diego, CA 92152-6800

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Memorial Sloan-Kettering
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1275 York Avenue
New York, NY 10021

Dr. Wallace Wulfeck, III
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Kentaro Yamamoto
Educational Testing Service
Rosedale Road
Princeton, NJ 08541

Dr. Wendy Yen
CTB/McGraw Hill
Del Monte Research Park
Monterey, CA 93940

Dr. Joseph L. Young
Memory & Cognitive
Processes
National Science Foundation
Washington, DC 20550

Dr. Anthony R. Zara
National Council of State
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625 North Michigan Ave.
Suite 1544
Chicago, IL 60611