Analysis of Multi-Component Educational and Training Needs

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Contexts

Context #1:
You are an instructional developer who has just been hired by a large teaching hospital as Director of Staff Training. You and your staff of three—all of whom have been in their positions for one to four years and all of whom have taught in assorted contexts, but none of whom has any particular instructional development skills—are expected to develop and implement "whatever training programs are necessary." Your budget is extremely small, and it becomes obvious, after a few weeks of intensive discussion with your staff, that the range and intensity of training problems is very wide. You know that you don't have a hope of attending to all training needs, given your resources, but worse, you lack a starting point because you don't know which needs are most critical.

Context #2:
Your institution has been awarded a contract by the government to develop a training program for managers of government-funded social housing (group homes, senior citizens' centers, live-in health care facilities, etc.). Simply put, although a few of the several hundred managers now in place have MBA's in administration, most have little or no formal training in the area—indeed, many have not even completed high school. They are expected to manage facilities housing anywhere from three to 800 people at varying levels of functionality, from completely self-sufficient to totally bed-ridden. One of the requirements of the contract is that you conduct a needs analysis to determine which training needs are most critical, then develop instruction to fill these needs.

Context #3:
A professional organization of computer specialists, whose membership is largely from the retail business, insurance, and banking sectors, but also includes manufacturing, wholesaling, and education, wishes to initiate a professional development education program for "all computer people in the province," but isn't sure where to begin. Each person on the executive produces a different list of topics that, according to his or her personal experiences, warrant professional development education. There is a vague feeling that despite the vast amount of learning about different hardware and software that constantly takes place in a computing environment, it is not so much computing that defines the *real* need as how to manage people, how to administer, how to deal with people. You have an opportunity to moonlight a lucrative contract with the organization, but first you have to show them that you are capable of addressing the most widespread professional development needs (even though you are not an expert in computing); to do so, of course, you must know what the needs are.

All three contexts show evidence of the necessity of conducting thorough needs assessments prior to undertaking other instructional development activities. And all three contexts are quite typical of the real world (e.g., see Spitzer, 1981).

The Need for an Analytic Tool

One approach to the assessment of educational or training needs involves a task analysis of the general job role, which leads to the specification of a series of skills or tasks[3] that individuals in that job role might be expected to be capable of performing (Misanchuk, Note 1). For each task or skill, the potential learner is measured on one or more of three criteria, called *need components*: the **competence** or ability of the individual to perform the task or skill, the **relevance** of the task or skill for the individual's particular job role[4], and the individual's **desire** to undertake training in the task or skill (Misanchuk, Note 1; Misanchuk & Scissons, Note 2).

While different institutions and organizations may use different combinations of those three need components to operationalize educational or training needs (see Misanchuk, Note 1), it is likely that at least two of the components will be included in any definition. This implies that two or three (typically numerical) responses for each individual, for each task or skill, must be considered simultaneously—a mind-boggling job if there are dozens of skills or tasks, and dozens or even hundreds or thousands of potential learners (e.g., Misanchuk & Scissons, Note 2; Scissons & Misanchuk, Note 3).

The adoption of a multi-component model of educational and training needs leads to the collection of two, and possibly three pieces of data per potential learner for each skill eligible for training. In any but the most trivial situation, this leads to a vast array of data whose complexity belies analysis by conventional methods.

The analysis of such needs data would be made considerably easier if it were possible to compute a single score for each potential learner, representing the two or three dimensions of each skill/task. Such scores could then be averaged across people to provide an index of need for each skill/task.

A number of approaches suggest themselves but turn out to be lacking. Let us assume for purposes of illustration that the data for two need components, relevance and competence, have been collected by having potential learners use five-point Likert-type scales to respond to the questions "How important is this task for your job role?" (1

= not important; 5 = very important) and "How well can you perform this task?" (1 = very poorly; 5 = very well).[5]

To begin with, there are very few analytic methods for ordinal data that would apply in this situation. Indeed, even the most sophisticated conventional analyses available would use tests for nominal data (thereby underusing the power available in the ordinal data at hand), and even those require the reduction of data collected on five-point scales to 2 X 2 tables (thereby sacrificing even more power) (Reynolds, 1977).

Measures of association (correlation) such as Kendall's Tau or Goodman and Kruskal's Gamma are unhelpful, since in the needs analysis context they would simply indicate degree of agreement of respondents to the two or three scales asking different questions. Proportions or percentages are an improvement over raw frequencies, but they are not very helpful in assimilating into one meaningful entity the 25 (for a two component function) or 125 (for the three component definition) data points associated with each individual skill/task.

The odds ratio (Reynolds, 1977) and the dichotomized-additive coefficient procedure devised by LeSage (1980) are somewhat better, but suffer the problem identified by Misanchuk (1980): the reduction of the data to a 2 X 2 format could cause fairly serious possibilities of misinterpretation.

Even if one were willing to subject the data to parametric statistical analysis (a somewhat dubious procedure, given the ordinal nature of the data), there is no convenient way to incorporate consideration of both the within-item variances and the between-item variance in a way the permits the eventual ranking of items (skills) in descending order of educational need. Misanchuk and Scissons (Note 2) attacked this problem in a less than satisfactory way by converting all average item responses to z-scores, using the pooled inter-item variance, then identifying those items as high need for whom all joint z-scores were over a certain arbitrary cutting point. The use of the cutting-points (for each of competence, relevance, and desire) was problematic, since, at best, it yielded only groups of items whose approximate need was the same; there was no satisfactory way to differentiate with respect to need among items within such a group.

The proportionate reduction in error (PRE) approach to the analysis of cross-classified ordinal data developed by Hildebrand, Laing, and Rosenthal (1977a, b) offers the potential for developing an analogue which could be applied to the needs analysis situation. In contrast to the typical methods of analysis of nominal and ordinal data (e.g., the raw error rate; the odds, or cross-product, ratio; phi-square; chi-square; and various correlation coefficients [see Reynolds, 1977]), which are descriptive, a posteriori approaches to analysis, the approach suggested by Hildebrand, et al., is predictive. In other words, it predicts the probability that certain combinations of a joint distribution will occur, then tests to see how closely the prediction matches the observations.

The logic of this prediction approach is eminently adaptable to the analysis of educational needs: One need only postulate that a high educational need exists when the respondents collectively exhibit (for the two-component case) a high job relevance with a concomitant low competence in the skill, and conversely, that a low educational need exists when there is a low job relevance with concomitant high competence. The postulate can be extended to include three or more components of need, if desired (see Misanchuk, Note 1).

The procedure yields a single statistic which succinctly describes the need as defined on both dimensions simultaneously, permitting the immediate and intuitively obvious comparison of various skill needs by comparing single numbers, each representing one skill need. It also permits statistical tests for determining the significance of differences, although the subject will not be further pursued in this paper (for details, see Hildebrand, et al. [1977a, b] and Reynolds [1977]). For the three-component definition of need, the adaptation of the procedure is not quite as straightforward; however, a number of possibilities are being actively investigated to permit the multivariate application.

The remainder of the paper shows how the interpretation of the PRE approach can be adapted to the needs analysis case if the postulate in the penultimate paragraph is accepted.

Theoretical Rationale

To highlight the relative simplicity of the logic of the PRE approach to analyzing educational needs, the two-component definition of need (competence and relevance) will be used in the following discussion, although obviously, any two need components could be substituted (see Misanchuk, Note 1); the logic of the three-component analysis, however, is directly analogous.

It is reasonable to say that the highest need exists for that skill in which all respondents show a great lack of competence coupled with a great job relevance, i.e., all respondents fall into cell (1,5) (see Figure 1). Stating this in prediction terms, we can say that we have made no error in predicting maximum need for a given skill if all respondents fall into cell (1,5). Still another way: cell (1,5) is an errorless cell, while all the other cells are error cells, i.e., respondents' choosing other cells gives us evidence that our prediction of maximum need is not completely true.

> In any but the most trivial situation, this leads to a vast array of data whose complexity belies analysis by conventional methods.

To what extent is it untrue? Obviously, if all but one respondent chose cell (1,5), the prediction of maximum need is very nearly true, whereas if only half the respondents did so, the prediction is less true. Similarly, if one respondent (or half of them) "erred" by choosing cells (1,4) or (2,5), or even (2,4), then the prediction is more nearly true than if the same number chose cells (1,1), (2,1), (5,4)—or even (3,3)—or some combination of them. As the number of respondents choosing cells remote from (1,5) increases, the degree of falsity of the prediction increases, until ultimately the prediction is maximally false when all respondents choose cell (5,1), indicating that the task has minimal job relevance coupled with maximal respondent competence.

Now, in reality, we would be unlikely to define only cell (1,5) as errorless. As already suggested, cells (1,4), (2,5), and (2,4) represent responses that lend a fair bit of credibility to the prediction of high need, albeit less than the situation where everyone responds in cell (1,5). We might therefore designate cells (1,5), (1,4), (2,5), and (2,4) as errorless cells, and all the others as error cells. Indeed, this is exactly analogous to what is done in the dichotomized-additive approach mentioned earlier. The problem with this strategy, as Misanchuk (1980) pointed out, is that it becomes impossible to differentiate between the situation where everyone is in cell (1,5) and the one where everyone is in one or more of cells (1,4), (2,5), and (2,4).

Ideally, we would like to recognize an increasing amount of error associated with cells that are progressively more remote from (1,5). The PRE approach allows us to do just that, by assigning error weights to cells representing "partial" errors: cell (1,5) is given an error weight of 0, cells (1,4) and (2,5) could be given error weights of, say, .1, and cell (2,4) could be given an error weight of .2, etc. Although different values could be assigned to the various error weights, it seems reasonable to have the "worst" error, cell (5,1), represented by an error weight of 1.0 (i.e., it is a "whole" error), and the other cells pro-rated reasonably as they become more proximate to the completely errorless cell (1,5). Any number of weighting schemes could be devised, but parsimony and simplicity being the essence of good theory, there seems no reason to apply anything more complicated than a linear progression; I suggest that the distribution of error weights shown in Figure 2 is a reasonable one to use while we learn more about the analytic method.

To understand the logic of the actual analysis, it is best to temporarily ignore the "partial" errors represented by the error-weighted cells and deal with the more straightforward case where responses are unequivocal. The hypothetical frequency distribution in Figure 3 will be used to trace the logic of PRE analysis; note that for this example, cells (1,4), (1,5), (2,4), and (2,5) are considered errorless.

For any pattern of response cells, it is possible to compute the number of expected respondents for each cell, based on the marginal totals for the distribution, in a manner very similar to that used in computing the familiar chi-square. The proportion of respondents expected for cell (2,2) in the distribution in Figure 3, for example, is

$$(9/45 \times 6/45) = .022.$$

For 45 respondents, this proportion corresponds to $.022 \times 45 = 1.2$ respondents that can be expected to fall into cell (2,2).

For cell (3,4) the expected number of respondents is

$$(9/45 \times 12/45) \times 45 = 2.4.$$

Using only the marginals, then, it is possible to compute the expected response rate for each cell, which we can then use (as chi-square, again) to compare to the observed response rate. In prediction terms, this expected response rate can be viewed as corresponding to the expected error rate due to chance. In practice, however, we are interested only in the cells where errors of prediction can actually be committed, so we say that the expected error for an errorless cell is 0. The expected error rate for the entire distribution is simply the sum of the expected errors for all error cells. For Figure 3, therefore, the expected error rate is

$$(13/45)\,(6/45) + (13/45)\,(6/45) + (13/45)\,(9/45) + 0 + 0 + (9/45)\,(6/45) + (9/45)\,(6/45) + (9/45)\,(9/45) + 0 + 0 + (9/45)\,(6/45) + (9/45)\,(6/45) + (9/45)\,(9/45) + (9/45)\,(12/45) + (9/45)\,(12/45) + (7/45)\,(6/45) + (7/45)\,(6/45) + (7/45)\,(9/45) + (7/45)\,(12/45) + (7/45)\,(12/45) + (7/45)\,(6/45) + (7/45)\,(6/45) + (7/45)\,(9/45) + (7/45)\,(12/45) + (7/45)\,(12/45) = 1497/2025 = 0.739.$$

	Not Important		Relevance		Very Important
Very Poorly	(1,1)	(1,2)	(1,3)	(1,4)	(1,5)
Competence	(2,1)	(2,2)	(2,3)	(2,4)	(2,5)
	(3,1)	(3,2)	(3,3)	(3,4)	(3,5)
	(4,1)	(4,2)	(4,3)	(4,4)	(4,5)
Very Well	(5,1)	(5,2)	(5,3)	(5,4)	(5,5)

Figure 1. Cell labels in a tabular display of bivariate data. Cells are identified according to convention by numerically identifying the row first and the column second, separated by a comma, and enclosed in parentheses.

Now, in fact, the observed error rate is different from the expected one: It is represented by the sum of the proportions of observations actually falling into error cells; once again, errorless cells are excluded from the computation since entries in them do not constitute errors. For Figure 3, the observed error rate is

$$1/45 + 2/45 + 1/45 + 0 + 0 + 1/45 + 1/45 + 2/45 + 0 + 0 + 2/45 + 1/45 + 3/45 + 2/45 + 1/45 + 0 + 1/45 + 2/45 + 3/45 + 1/45 + 2/45 + 1/45 + 1/45 + 2/45 + 1/45 = 31/45 = 0.689.$$

The proportionate reduction in error is defined by Hildebrand, et al. (1977b) as the relative reduction in error achieved by the predictions in comparison to the error of a reference position. To fulfill this definition, the number of errors that could be expected, based on knowledge of marginal distributions only (the reference position), is compared to the actual, observed distribution of errors.

	Not Important		Relevance		Very Important
Very Poorly	.7071	.5303	.3536	.1768	0.0000
Competence	.7289	.5590	.3953	.2500	.1768
	.7906	.6374	.5000	.3953	.3536
	.8839	.7500	.6374	.5590	.5303
Very Well	1.0000	.8839	.7906	.7289	.7071

Figure 2. Suggested error weights. For simplicity, a more-or-less linear progression (based on a unit diagonal length) is suggested, although other patterns could be proposed for specific purposes. For all practical purposes, weights could be rounded to two significant figures.

The statistic del, ∇, is used by Hildebrand, et al. (1977a, b) to represent the proportionate reduction in error.

$$\nabla = \frac{\text{Expected errors - Observed errors}}{\text{Expected errors}}$$

For Figure 3,

$$\nabla = \frac{.739 - .689}{.739} = .068$$

In more formal terms,

$$\nabla = 1 - \frac{\sum_{i=1}^{R} \sum_{j=1}^{C} W_{ij} P_{ij}}{\sum_{i=1}^{R} \sum_{j=1}^{C} W_{ij} P_{i.} P_{.j}} \tag{1}$$

where W_{ij} is the error weight for cell (i,j) ($W_{ij} = 1$ for every "whole" error cell; $0 < W_{ij} < 1$ for every "partial" error cell), P_{ij} is the probability of a randomly sampled observation falling into cell (i,j), and $P_{i.}$ and $P_{.j}$ are the expected marginal probabilities for the rows and columns, respectively. Examination of the equation immediately above shows how the "partial" errors mentioned earlier can be accommodated by the statistic: substituting the error weights suggested in Figure 2 for the W's in the equation gives the desired result.

In the needs analysis situation, as distinct from the prediction situation, it makes more sense to assume some prior knowledge of the expected distribution than to allow the observed marginal probabilities to determine the expected distribution.[6] If the marginal probabilities are known, the denominator of (1) becomes defined independently of the observed data; individual cell probabilities, of course, are simply the product of the row and column probabilities corresponding to that cell.

To distinguish the original statistic proposed by Hildebrand, et al. (1977a, b) from the one conceptualized here (with its prediction of high need concomitant with an error weight distribution similar to that in Figure 2 and its known expected distribution) we shall attach the subscript N to the original statistic. In other words, ∇_N, the proportionate reduction in error index of educational need, is (computationally) equivalent to equation (1) (with the proviso that $P_{i.}$ and $P_{.j}$ are previously specified by the researcher).

Interpretation of the Statistic

The adaptation of the PRE approach to needs analysis involves predicting a high educational need for each skill, then using the computed value of ∇_N to determine the validity of the prediction. A high value of ∇_N indicates high validity of the prediction, hence high educational need for the associated skill. Comparative values of ∇_N, therefore, can be colloquially interpreted as comparative degrees of need.

Perhaps the most useful feature of ∇_N is that it is a single number which can summarize information about the distribution of two or more variables. Del can assume a range of values from minus infinity to 1. Negative values, which denote a prediction failure in the prediction application, can, in the needs analysis situation, be immediately and intuitively regarded as indicating no need. Positive values near zero indicate a small need, and values approaching 1 indicate increasing need. The individual value of ∇_N associated with a skill, per se, however, is of less interest than when it is taken in comparison to the values of ∇_N associated with other skills: a ranking of needs based on the ranking of values of ∇_N is thus possible.

In that regard, an interesting area for further research is the question of prior knowledge of the expected marginal distributions. A number of reasonable distributions can be postulated: flat, normal, and monotonically increasing distributions represent only three of them. While the absolute values of ∇_N will obviously change as the values of $P_{i.}$ and $P_{.j}$ are changed, it would be interesting to find out whether or not judgments about needs would change as a function of the expected marginal distributions. For example, ∇_N for Figure 3, if an expected probability distribution of .2, .2, .2, .2, and .2 is assumed for the marginals of both variables and the error weight distribution of Figure 2 is used, equals .184. If the expected probability distribution is assumed to be approximately normal, and thus the probabilities .036, .238, .451, .238, and .036 are used, the value of $\nabla_N = .128$. If one makes the assumptions that the task analysis underlying the needs assessment process should have ensured that the tasks used as a basis for the needs identification procedure were, by and large, quite relevant to the job roles, and that the process of natural selection that obtains in hiring and firing tends to place more-or-less competent individuals into job roles, it might be reasonable to postulate a monotonically increasing set of proportions as one moves away from the upper left corner of the needs assessment data matrix. An expected probability distribution which fulfills that description, 0, .1, .2, .3, .4, yields a value of $\nabla_N = .220$.

To provide a flavor of what values of ∇_N can be expected from various distributions, and to indicate the kind of changes that can be expected from varying the expected distribution, Table 1 presents some comparisons based on the data in the matrices in Figure 4.

Matrix [1], as is visually apparent, illustrates a high need, and has a correspondingly high value of ∇_N.

As might be expected, the values of ∇_N decrease as we go from Matrix [1] to Matrix [6]. Matrix [5], which illustrates virtually no need, and Matrix [6], which illustrates no need at all (according to visual inspection), have negative values of ∇_N.

While there are differences in values of ∇_N as a function of expected distribution used, the monotonicity of the values across the six matrices is retained, and it is probable that any of the expected distributions could be assumed without destroying the ability of the statistic to be used at least to rank order educational needs. It would be advantageous, however, to have a standardized approach to the analysis of educational needs, and the reasonable assumptions above about the natural selection process in effect when people get placed into job roles and the unlikelihood of identifying irrelevant tasks during the task analysis argue well for the monotonically increasing set of marginal probabilities: 0, .1, .2, .3, .4. Accordingly, I suggest these probabilities as reasonable ones to use while we gain more experience with the statistic.

Practical experience with the statistic, albeit limited, indicates that high values of ∇_N (i.e., values approaching 1) are not

The procedure yields a single statistic which succinctly describes the need as defined on both dimensions simultaneously.

common in needs analysis: in a recent study (Scissons & Misanchuk, Note 3), values of ∇_N did not exceed about .25. Realistically, the typical maximum values of ∇_N ought not to be expected to be much higher than that, for the same reasons as those listed in the argument for the 0, .1, .2, .3, .4 marginals: the tasks used as a basis for the needs assessment procedure were, by and large, quite relevant to the job roles, and the process of natural selection that obtains in hiring and firing tends to place more-or-less competent individuals into job roles.

Competence	Not Important		Relevance		Very Important	
Very Poorly	1	2	1	2 *	7 *	13
	1	1	2	3 *	2 *	9
	2	1	3	2	1	9
		1	2	3	1	7
Very Well	2	1	1	2	1	7
	6	6	9	12	12	45

Figure 3. Hypothetical frequency distribution of responses. Asterisks (*) indicate errorless cells.

Competence	Not Important		Relevance		Very Important	
Very Poorly				2	39	41
				2	2	4
Very Well						
				4	41	45

Figure 4(a). Matrix [1].

Competence	Not Important		Relevance		Very Important	
Very Poorly			2	2	29	33
			2	2	2	6
			2	2	2	6
Very Well						
			6	6	33	45

Figure 4(b). Matrix [2].

Competence	Not Important		Relevance		Very Important	
Very Poorly			2	6	15	23
			2	8	6	16
			2	2	2	6
Very Well						
			6	16	23	45

Figure 4(c). Matrix [3].

Competence	Not Important		Relevance		Very Important	
Very Poorly	2		6		15	23
	2		8		6	16
Very Well	2		2		2	6
	6		16		23	45

Figure 4(d). Matrix [4].

Competence	Not Important		Relevance		Very Important	
Very Poorly	2		2		2	6
	6		8		2	16
Very Well	15		6		2	23
	23		16		6	45

Figure 4(e). Matrix [5].

Competence	Not Important		Relevance		Very Important	
Very Poorly						
	2	2	2			6
	6	8	2			16
Very Well	15	6	2			23
	23	16	6			45

Figure 4(f). Matrix [6].

The possibility of assigning different error weights to cells poses interesting possibilities for research. It also provides for flexibility in varying the emphasis on the need of one or more of the need components, thereby overcoming a major limitation of both the approach used by Misanchuk and Scissons (1978) and the dichotomized-additive approach (LeSage, 1980). If there were a priori reason to believe that, say, competence and relevance were of equal importance in determining need but that desire was only half as influential as the other two components, the PRE approach could accommodate it. Furthermore, it may be possible to sharpen the sensitivity of discrimination at the high end by using a weighting scheme other than the linear one suggested in Figure 2.

As noted earlier, the multivariate extension of the statistic is currently being investigated. For the bivariate case, it does not matter (in the prediction situation) which of the two is considered the dependent and which the independent variable. This property makes the statistic directly applicable to the needs analysis situation, for the bivariate case. However, the property does not hold for the multivariate case; hence the lack of straightforward adaptation mentioned earlier.

Computer programs have been developed for the procedure, making it easy to use; the computation of the statistic is well within the scope of a pocket calculator, however, and becomes laborious by that method when the number of distributions to be examined is large.

Conclusion

The adaptation of a proportionate reduction in error approach to the analysis of needs assessment data is relatively straightforward. In addition to permitting a greater sensitivity to differences in frequency distributions than other analytic approaches while providing a single statistic, ∇_N, for the comparison of bivariate distributions, there is a potential for extension of the statistic

Table 1

Effects on ∇_N and the Standard Error of ∇_N of Using Different Known Marginal Distributions.

	∇_N			SE_{∇_N}		
DISTRIBUTION[1]	FLAT	NORMAL	MONO	FLAT	NORMAL	MONO
MATRIX[2]						
[1]	.9552	.9488	.9543	.0187	.0200	.0179
[2]	.7939	.7795	.8029	.0452	.0484	.0432
[3]	.6785	.6560	.6926	.0408	.0436	.0390
[4]	.3570	.3121	.3851	.0815	.0872	.0780
[5]	−.2964	−.3869	−.2397	.0716	.0766	.0685
[6]	−.5178	−.6237	−.4513	.0374	.0400	.0357

[1]The FLAT distribution had marginal proportions of .2, .2, .2, .2, .2. The NORMAL distribution had marginal proportions of .036, .238, .451, .238, .036. The MONOtonic distribution had marginal proportions of 0, .1, .2, .3, .4.

[2]See Figure 4.

to the multivariate case. A scheme of error weights specified by the researcher permits differential weighting of need components, although a standard one proposed. The researcher must also specify the expected distribution of responses, and again, a standard distribution is proposed. Although experience with application of the procedure is still limited, its apparent advantages make it the method of choice for the analysis of two-component needs assessment data.

Reference Notes

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Footnotes

1. This paper was originally presented at the Annual Meeting of the Association for Educational Communications and Technology, Dallas, Texas, May 2–7, 1982, under the title *The Analysis of Multi-component Training Needs Data.* Portions of this paper were presented earlier at the Evaluation Network/Evaluation Research Society Joint Annual meeting, Austin, Texas, October 1–3, 1981, under the title *A Proportionate Reduction in Error Approach to the Analysis of Needs Identification Data.*

2. The author gratefully acknowledges the comments and suggestions made on earlier versions of this paper by R. A. Yackulic, R. A. Schwier, E. H. Scissons, A. T. Wong, and W. R. Foshay.

3. For lack of a better term, the terms 'task' and 'skill' will be used in this paper to mean approximately the same thing: a job-related activity that can be learned. Obviously, the words are used with considerably less precision in meaning than in most other applications in instructional development. Neither term is intended to imply only psychomotor activities. Tasks or skills—as the terms are used here—include everything from specific psychomotor activities to complex groups of activities that may involve cognitive and/or psychomotor (and perhaps even affective) components. For example, while 'typing at 60 wpm' would certainly qualify as a skill under the definition used here, so would 'preparing an income tax return,' or 'counseling employees.' Equally, the terms are meant to apply to such multi-faceted activities as 'using computers,' and to 'wage and salary administration.'

4. Despite the fact that one might assume automatic relevance for any skill identified by the task analysis, experience has shown that for any "homogeneous" group of any substantial size, there will be sufficient variability in job roles that asking the relevance of the skill is not gratuitous. This phenomenon is due to the high level of generality in the terminology used in the task analysis, which, in turn, is necessary because of the wide diversity of activities and job roles under investigation in situations such as those described in the **Context** section.

5. Full recognition is given to the possible shortcomings of self-report data vis-a-vis validity (e.g., see Pennington, 1980, p. 5-6), but the analytic method described below applies no matter how the data were generated.

6. This point was initially suggested by R. A. Yackulic.