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ABSTRACT

Data accumulated over two years were analyzed in order to evaluate two components of a teacher education curriculum--performance objectives and self analysis skills. A multi-step procedure was devised and implemented which uses regression to illustrate the feasibility of implementing the procedure for curricular decision making. This procedure provides an empirical rationale for assigning decision-weights to variables and illustrates how to combine the weighted variables to render a decision regarding the effectiveness of a curricular component. A number of evaluation models are briefly discussed. (Author/CTM)

Curriculum Decisions using Decision Weights
An Empirical Basis for Product Evaluation

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This project was undertaken to integrate mathematically data collected over two years to evaluate a curriculum. A multi-step procedure was devised and implemented which uses regression procedures to generate decision weights for variables included in the decision expressions. Longitudinal data related to two curriculum components were examined to illustrate the feasibility of implementing the procedure for curricular decision making. This procedure provides an empirical rationale for assigning decision-weights to variables and illustrates how to combine the weighted variables to render a decision regarding the effectiveness of a curricular component.

Comprehensive curriculum evaluation is a very complex process. This assertion is reasonable for no other reason than the variety of variables, such as the following, that must be attended to: learner achievement, interpersonal communications, power structures, school organizational climates, variety and quality of instructional resources available, and societal norms concerning education. With such a variety of concerns vying for attention, an evaluation project must define evaluation and differentiate the goal from the functions if the evaluation process is to contribute to the curriculum under scrutiny. In an oft-cited work, Scriven (1967) defined evaluation as a methodological activity in the following manner.

> "The activity consists simply in the gathering and combining of performance data with a weighted set of goal scales to yield either comparative or numerical ratings and in the justification of (a) the data gathering instruments, (b) the weighting and (c) the selection of goals." (p. 40)

Expanding on this definition, Scriven stated that evalaution should not only collect and analyze data, but should make judgments and report these judgments publicly.

Another significant definition of evaluation was developed by the Phi Delta Kappa National Study Committee on Evaluation (Stufflebeam, 1971):

> "Evaluation is the process of delineating, obtaining and providing useful information for judging decision alternatives." (p. XXV)

In contrast to Scriven, the authors of this definition emphasize that evaluation is a continuing process which provides information that should guide decision making, not produce judgments. The authors of these respective definitions agree that evaluation is a process whereby

data are gathered for the purpose of decision making, but disagree on who is to make the decisions. The issue of who makes the decisions may not be central if the scope of the curriculum evalaution is limited to a small scale project and the curriculum developers are also serving as evaluators. When curriculum development and subsequent evaluation of the curriculum occurs in educational settings whether at the local district or building level, or within higher education at the college or department level, the developer and evaluator roles may be assumed by the same individuals. It is assumed that under these circumstances the curriculum is being designed for a particular educational setting with no grandiose plans for marketing the curriculum regionally or nationally. Under these conditions, decision making in regard to the effectiveness of curriculum components is a viable goal and violates neither Scriven's nor the PDK committee's formulations of the concept "evaluation."

With an evaluation goal in mind, attention must be directed to the functions of the evaluation process. These functions may be directed either to the development, execution, and implementation of a curriculum or to the political and economic support for the curriculum (Zais, 1976, p. 377). Because of the different emphases that are possible, it is difficult to develop a single generalized model for curriculum evaluation. On a positive note, however, numerous conceptual models outlining various types of evaluation have been advanced during the past decade. For example, the Countenance Model (Stake, 1967), Formative and Summative Evaluation (Scriven, 1967), the Modus Operandi Method (Scriven, 1974), the CIPP (Context, Input, Process, Product) Evaluation

Model (Stufflebeam, et al, 1971), the Discrepancy Model (Provus, 1971), and the Center for the Study of Evaluation (CSE) Model (Alkin, 1974) are among the more familiar models. These models identify critical decision-making points along the continuum of processes occurring in curriculum development, particularly, the development sequence championed by Tyler (1950) and sustained by Taba (1962).

Once a model is selected or created from the theoretical constructs provided by the various models, the evaluator is faced with pragmatic issues of identifying appropriate instrumentation, selecting the sample, and analyzing the data. In his definition of evaluation, Scriven refers to the issue of combining data with weighted goal scales to produce numerical ratings and to the justification of those "weightings." This weighting construct is intriguing and should influence data analysis significantly. Weighting the data sources in terms of their relative importance prior to data collection appears to be what Scriven is suggesting when he discusses the primary, secondary, and tertiary effects of the curriculum on the various actors affected by the curriculum. The effects of the materials on the learners' mental and nonmental abilities and attitudes are labeled as the primary effects of the curriculum. Secondary effects of the curriculum affect those individuals who implement the curriculum, namely, teachers, teacher aides, supervisors, while tertiary effects are those effects on the school or other students brought about by learners or teachers who exhibit the primary or secondary effects (Scriven, 1967, pp. 74-82).

If primary effects such as achievement data, attitude data, and subsequent follow-up information are obtained from learners, should

all of these data sources have equal weightings? Moreover, if secondary effects, such as supervisor and/or principal ratings of program effectiveness are collected and combined with the primary effects, what "weights" should these data sources assume? Rather than assign decision weights a priori, this project was undertaken to develop a procedure whereby various data were collected, treated to determine decision weights, then combined in a mathematical decision equation. Specifically, the development and implementation of a procedure to empirically weight the data was an ancillary goal of this project, while the primary goal was the mathematical integration of weighted data to evaluate the quality of curriculum components.

Mathematical Decision Making - Two Examples

In these illustrations, a three phase collection plan was implemented to obtain longitudinal data from a competency based teacher preparation program. Both the data collection plan and the curriculum are discussed elsewhere (Denton, 1977). It is felt however, that the techniques described herein for producing decision expressions can be generalized to other settings and curricula.

Two curriculum components, namely, performance objectives and self analysis skills, were selected from the curriculum to demonstrate the statistical techniques and computational procedures used to yield decision weights and ultimately, the respective decision equations. Given the nature of the collection plan, a large number of variables (174) resulted for each indiviudal in the sample. However, logical relations between variables from each phase of the collection plan and the criterion variable (candidate achievement measure/instructional

unit) reduced the number of potential predictors for each curriculum component to a manageable number, namely, seven for the performance objectives unit and nine for the self analysis skills unit.

The initial statistical treatment involved the RSQUARE procedure from the Statistical Analysis System (SAS) (Barr and Goodnight, 1972). This procedure performed multiple regressions to the dependent variable with the predictors identified in the preceding step. Maximum variance (R^2 = .367) was accounted for by incorporating all seven of these variables for the curriculum component dealing with performance objectives:

Type of Variable	Symbol	Description of Variable
Criterion	ACHB	Candidate achievement value for performance objective curriculum component. Numerical value represents the number of objectives achieved by the former candidate over this topic.
Predictor	RECYB	Number of remediation attempts initiated by the candidate during the curriculum component on performance objectives.
Predictor	CS18	Classroom Supervisor of Student Teacher rating on the relation of test items to performance objectives both of which were developed by the candidate during his student teaching experience.
Predictor	CSBT	Classroom Supervisor of Student Teacher combined ratings on the development and use of performance objectives by the teaching candidate during his student teaching experience.
Predictor	US18	University Supervisor of Student Teacher rating on the relation of test items to performance objectives, both of which were developed by the student teacher.
Predictor	USBT	University Supervisor of Student Teacher combined ratings on the development and use of performance objectives by the teaching candidate during the student teaching experience.

Type of Variable	Symbol	Description of Variable
Predictor	IT	Combined follow-up survey ratings from first year teacher (former candidate) on the importance of using performance objectives in planning and conducting instruction.
Predictor	PT	Combined follow-up survey ratings from first year teacher (former candidate) on the effectiveness of the preparation program to impart skills of objective development for use in planning and conducting instructional units.

In the case of the curriculum component on self-analysis skills, optimal variance (R^2 = .378) was produced by the following five variables:

Type of Variable	Symbol	Description of Variable
Criterion	ACHE	Candidate achievement value for self-analysis curriculum component. Numerical value represents the number of objectives achieved by the former candidates.
Predictor	RECYE	Number of remediation attempts initiated by the candidate during the curriculum component on self-analysis skills.
Predictor	CS28	Classroom Supervisor of Student Teacher rating on the candidate's ability to self-analyze his instructional skills.
Predictor	CSLT	Supervisor of Student Teacher combined ratings on the candidate's ability to use verbal interaction analysis and classify teacher questions for purposes of instructional analysis.
Predictor	IET	Combined follow-up survey ratings from first year teacher (former candidate) on the importance of self analysis of instructional skills to plan a variety of activities.
Predictor	PET	Combined follow-up survey ratings from first year teacher (former candidate) on the effectiveness of the preparation program to impart the skills of self-analysis for curriculum planning purposes.

These respective predictor-dependent variable sets for the performance objectives and self-analysis skills curriculum components were subsequently analyzed by simple correlational techniques. This procedure was undertaken to determine the degree of independence among predictors within each set of variables. Tables 1 and 2 present correlation tables of the variables for each of the curriculum components. These tables reflect instances of substantial intercorrelations between predictors, (IEP-PLT, CSLT-CS28 in Table 1; CS18-CSBT, US18-CSBT, USBT-CBST, US18-CS18, US18-USBT, IT-PT, USBT-CS18 in Table 2). These variables were not removed from the predictor dependent variable sets at this point, but concern for the possibility of suppression variables being present in the respective variable sets was heightened. Suppression variables result when two or more predictors are sufficiently intercorrelated and have quite different correlations with the dependent variables; and while the suppression variable may increase the total variance of the model, the interpretation of the unique contribution of this variable to the model is not clear. Moreover, the existence of a suppression variable is signalled when the sign of its regression coefficient is opposite the sign of its simple correlation with the criterion (Garms, Note).

Insert Tables 1 & 2

Subsequent to the correlation analysis, a regression procedure, entitled maximum R-SQUARE improvement, was used to produce prediction models for the two curriculum components under consideration. This procedure first finds the one variable model producing the greatest R^2 value. Then

another variable, one which will yield the greatest increase in variance accounted for, is added. After the two-variable model is obtained, each of the variables in the model is compared to each variable not in the model. This procedure determines if removing the variable in the model and replacing it with the excluded variables will increase R^2. This comparing-and-switching process is repeated until the optimal arrangement of predictions in the model are found (Barr and Goodnight, 1972). Results of these analyses are presented in Tables 3 and 4. The F values for both regression models were determined to be significant, namely, $F = 2.65$, p .03 (performance objectives), and $F = 3.29$, p .02 (self-analysis skills).

Insert Tables 3 & 4

The probable existence of suppression variables in the regression models was initially realized when the correlation analyses were conducted among the variables in the two data sets. Confirmation of their existence, resulted however, when the sign of the beta value of each predictor was compared with the sign of the correlation coefficient between the predictor and dependent variables. Suppression variables identified in this manner included USBI and CS18 from the performance objectives curriculum component, and CS28, IIT, and RECYL from the self-analysis skills unit. Because of this finding, these variables were omitted from further consideration since the variance attributed to suppression variables defies explanation.

The regression procedure implemented for the prediction models produced partial sums of squares for each surviving predictor which

became the importance weights for the remaining variables in the decision equations. Substituting these values into the generalized expression, $Y \min = \sum_{i=1}^{n} w_i X_i$, produced the following decision equation for the performance objectives component:

$$Y \min = 3.15 \bar{X}_{US18} + .57 X_{IT} + .24 X_{PT} + .54 X_{LBSI} + .16 X_{RECYB}$$

while the decision equation for the self-analysis skill component assumed the form:

$$Y \min = 7.17 X_{CSET} + 3.56 X_{PET}.$$

Substituting the mean values (Table 5) for each variable in each equation and performing the arithmetic operations yielded 31.48 for the performance objectives curriculum component and 97.65 for the self-analysis skill curriculum component. These values were compared with criterion values (Y min) calculated for each equation based on maximum values for each decision variable (Table 5) multiplied by a .75 accomplishment factor. The resulting criterion values for the performance objectives component was 30.64 while the cut-off value for the self-analysis skills component was 120.71. Clearly, the calculated value for the self-analysis component (97.65), did not reach the criterion value of 120.71. Conversely, the calculated value (31.48) for the performance objectives component exceeded the cut-off value of 30.64. Comparing the magnitudes of the calculated decision values (ΣIX) with the respective criterion values (Y min) for each component justifies: the decision to extensively revise or delete the curriculum component on self analysis skills, and the decision to retain the performance objectives component in the

curriculum without modification.

Discussion

A cursory examination of the results of these analyses suggests that the goals of this project were achieved. However, a number of assumptions, observations, and decisions were made which heretofore have not been addressed. First, curriculum evaluation as practiced here assumed the performance objective to be the basic organizational element in curriculum design. Instructional activities and assessments were directly related to performance objectives in the various components, thereby allowing these curricular elements to be isolated for evaluation.

Second, another assumption of this project was that candidate achievement data obtained from criterion-referenced tests could serve ...al functions. One function of the data was to provide course progress indicators for the candidate's course grade, while the second function was to evaluate the effectiveness of curriculum components related to particular objectives. In the case of student progress, assessment data were treated idiographically, that is, the candidate was the unit of analysis. However for the second function, program evaluation, the achievement data were treated normatively. This data set was thought to be most appropriate for the criterion variable used in deriving the weights for the decision equations because of the relation of these data to the instructional components, and because of the careful attention and thought afforded the tests by the candidates. Moreover, Scriven's position on payoff evaluation (1967, pp. 59-62) lends credence to the application of an achievement data set as the

criterion variable in the decision process.

Third, only endogenous variables, those which occur as a result of events within the curriculum, will be considered as potential elements in a curriculum decision equation. The logic of this decision rests on the idea that adjustments of the curriculum can influence the magnitude of these variables, whereas exogenous variables, such as personality traits of an individual which are external to the curriculum, cannot be modified by changes in the curriculum.

Fourth, considerations for weighting the data ranged from intuitively assigning decision weights to devising a multi-step procedure which provides empirical justification for the assigned weights. Since the data available afforded numerous variables, and the criterion variable was known, regression procedures were considered viable for quantifying the "weighting" process. Regression procedures are relatively free of operational assumptions, and may be readily employed given appropriate computer software, namely, user oriented statistical packages. Further, maximum R^2 improvement regression analysis yields two important elements in weighting the data:

a) the partial sums of squares values which indicate the unique contribution of each predictor to the overall variance in the regression model (Draper, Smith, 1966).

b) beta values for each variable which serve to verify whether that predictor is a suppressor variable (Garms, 1968).

Fifth, the generalized first order linear equation, $Y \min = \sum_{n=1}^{i} I_{xi} X_i$, for evaluating the curriculum components resulted after considering whether transformations of the data sets (reciprocal,

logarithmic, square root, and higher order models (X^n)) would enhance the decision equations. For these adjustments, the appropriate choice should be made on the basis of previous knowledge about the effect of the transformation on the variable. Usually, this condition is not known, for example: What is the instructional significance of using the natural logarithm (ln^e) of a supervisor's numerical rating? Or how does this transformation influence the statistical analysis? These questions illustrate potential unknown effects of possible data transformations. In addition, the linear regression which yields the decision weights will not be statistically significant if the first order model digresses too far from linearity. Because of these observations, the decision was made to use the generalized expression with first order variables rather than resort to data transformations which would increase the complexity of the equations.

Finally, the relations of decision variables to the criterion were limited to the range of observations from which the decision weights were derived. The significance of this observation is that each time a curricular component is to be evaluated a unique decision equation must be developed.

In view of these assumptions, observations, and limitations of the evaluation process, one may question whether the project goals were actually achieved. To resolve this concern, reconsider the primary goal of the project and the steps taken to accomplish it. Essentially, the goal called for the mathematical integration of weighted data into decision equations for curricular evaluation. The following procedures were developed to accomplish this goal:

1) Identifying potential decision variables - This step is accomplished by determining the logical predictors among the array of predictor variables that are available.
2) Selecting decision variables - A multiple correlation procedure incorporating the variables identified in step one is performed with the criterion variable to determine the "optimal combination" of decision variables. This "optimal combination" depends on the axiom, maximum variance with minimum variables.
3) Checking Relation Among Predictors - Simple correlation coefficients are calculated among all variables identified in Step 2. This procedure is undertaken to determine the degree of independence among predictors. High correlations between predictors indicate a violation of the assumption of regression procedures, i.e., independence of predictor variables, and signals the prospect of suppression variables.
4) Determining decision - weights - A regression procedure is conducted with the decision variables identified in Step 2. This procedure yields an overall F-test for the regression model, as well as F values for each decision variable in the model. If the overall F value is not significant, indicating the variance accounted for by the decision variables is slight or the regression is not linear, the process to determine a decision equation terminates at this point for the instructional component under consideration. Conversely, if the overall F value is significant, the decision

weight for each variable assumes the numerical value of the partial sums of squares for that variable. The directionality (arithmetic sign) of the decision weight assumes the sign of the beta value for the variable provided the sign of the simple correlation between that variable and the criterion correspond to the sign of the beta value.

5) Incorporating decision weights into a decision equation - The decision weights resulting from the regression procedure are then substituted into the general expression $Y \min = \sum_{n=1}^{i} I_{xi} X_i$ to complete the decision equation.

6) Solving decision equation - The expression on the right side of the equation is solved by adding the products of the respective decision weight - variable means together. The expression Y min is determined in much the same manner except maximum values replace the mean values. The resulting sum is then multiplied by a .75 accomplishment factor. This value was selected as the accomplishment factor because of potential positive bias on rating scales and perception instruments, and the intuition that an instructional program should not be considered effective unless it is compared with a fairly rigorous but attainable standard. Interpretation of the results of these calculations depend on the relative magnitudes of the solutions; if the value of Y min exceeds the value on the right side of the expression revision of the instructional component should be seriously considered.

That these steps represent a functional process depends on whether

implementation has occurred and yielded results which are meaningful. Results of the evaluations included in this paper have illustrated that indeed these steps are feasible and do provide empirical support for curriculum decisions. In essence, this project has operationalized the integration of longitudinal data sets into a generalized mathematical expression for rendering precise curricular decisions.

Table 1

Correlation Matrix of Predictor and Dependent Variables
in Decision Structure for Self Analysis Module

	ACHE	RECYE	CS28	CSET	IET	PET
ACHE	—					
RECYE	-.03	—				
CS28	.07	.13	—			
CSET	.12	.09	.55	—		
IET	.05	.12	.11	.10	—	
PET	.32	-.31	.16	.04	.58	—

ACHE - Criterion Variable

Table 2

Correlation Matrix of Predictor and Dependent Variables
in Decision Structure for Performance Objectives Module

	ACHB	CSBT	USBT	IT	PT	REFYB	CS18	US18
ACHB	—	.13	.06	.12	.22	.00	.27	.47
CSBT		—	.86	-.03	.04	.07	.77	.51
USBT			—	-.01	-.02	.02	.46	.61
IT				—	.47	-.02	.03	.00
PT					—	-.02	.13	.15
REFYB						—	-.05	.00
CS18							—	.56
US18								—

ACHB = Criterion variable

Table 3

Maximum R^2 Improvement Regression Procedure for the Dependent Variable: Learner Achievement on the Performance Objectives Instructional Component

Source	Df	SS	MS	F	Prob	R^2
Regression	7	6.024	.861	2.654	.03	.367
Residual	32	10.376	.324			
Total	39	16.400				

Source	Partial SS	b value
HS18	3.15	.67
IT	.57	.07
PT	.24	.05
USBT	.20	-.03
CSBT	.54	.03
CS18	.47	-.29
PTGYB	.16	.05

Table 4

Maximum R^2 Improvement Regression Procedure for the Dependent Variable: Learner Achievement on the Self-Analysis Skills Instructional Component

Source	Df	SS	MS	F	Prob	R^2
Regression	5	11.311	2.262	3.290	.02	.380
Residual	27	18.568	.688			
Total	32*	29.879				

Source	Partial SS	b value
CSET	7.17	.17
PET	3.56	.16
CS28	2.19	-.40
IET	.40	-.05
PECYE	.08	.06

* Missing data reduced the sample of this regression.

Table 5

Means and Maximum Values of Independent Variables
Used in Decision Equations

Curriculum Components

Performance Objectives			Self Analysis Skills		
Variable	$\bar{X}$	Max X	Variable	$\bar{X}$	Max X
PECYB	1.47	5.0	CSET	8.47	15
HS18	4.48	5.0	PET	10.37	15
CSBT	21.10	30.0			
IT	6.88	10.0			
ST	7.53	10.0			

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