SOME CROSS-VALIDITY STUDIES INVOLVING THE COLLEGE ENTRANCE TEST

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Predictor set suppressor variables from the Gumban and Iledan (1971) study were analyzed for validity and the predictive efficiency of the College Entrance Test were interpreted in more simple statistical terms. Regression equations were developed and cross-validity performed on validation samples from different schools for the specific purpose of finding some indications of usefulness of the equations for prediction outside of the school population from which the derivation samples were obtained.

Tests as instruments for predicting student success in achieving specific academic goals fill a fundamental need in our educational system. But between their development and general acceptance lie the multiple and diversified statistical methods of proving their reliabilities and validities requiring repetitive analyses before decisions can be made as to the general usefulness of the tests. The Gumban and Iledan (1971) study on the College Entrance Test (CET) shows that the test has acceptable levels of predictive validities for a relatively homogeneous group of schools, and that it differentiates between sexes (Gumban, 1971) along certain dimensions of abilities.

It will not be wise to rest content on these findings because from the psychological point of view the "ideal" prediction scheme to optimally determine a student's potentialities is one that includes intellective as well as other variables that, in one way or another, affect academic success. Although the American experience tells us that the gain in multiple correlation is minimal (Fishman, 1961), i.e., a little over their .50 national average when only intellective predictors and college criteria are correlated, still such researches should and must be undertaken because the search for human talent cannot discount the effect of cultural and personality factors.

A student's aptitude and intelligence scores give us no more than an inkling of his talent and should not be made the sole determinant of his success in college, but too often this is violated. We place too much importance on being in the upper 10 per cent, or in being one of the ten highest performers in an examination, and lose sight of the fact that success is not wholly dependent on intellectual capacity as measured by such tests but is influenced by antecedent and personality factors as well. Talent, in its broader sense, embraces not only intellective and cognitive processes but also creative, emotive and motivating forces in a man (McKinnon, 1960). Demographic, socio-economic and transactional factors have also their effects, the latter having to do with the relationship between the student and his academic environment, i.e., for a school that has set up its standard of performance for success, the criteria are the student's psychological characteristics (Stein, 1963).

However, the use of intellective and achievement measures still play a major role in predicting academic success since there is yet to be found a better way of *initially* assessing a student's potentialities. One very important concern of counselors, therefore, is the prediction of an entering freshman's academic performance based partly on high school grades and/or scores on an entrance test, if the latter is required by the school.

Some schools in the Philippines that have felt the need for optimizing student performance in their respective campuses, and out of it, for reasons of economy in time, money and manpower, have adopted foreign-made tests or have developed their own. One objection to the use of these foreign tests is that some of the items in them have a cultural bias, i.e., they will favor examinees oriented to that same culture, although some of these tests may not be entirely useless in the hands of counselors well-informed in cultural differences (Bulatao, 1966).

As for a test developed in an institution, the test may have limitations. For one, the predictive properties of the test will only be valid for that school, and for as long as the type and homogeneity of its freshman entrants will remain the same. But a school that has unstable population characteristics, because its students come from different corners of the country from year to year, will find difficulty in ensuring a maximum output of graduates with the right training if it follows these methods of screening. And yet, viewed from outside the institution these are minor problems compared to the unsettled question of heterogeneity among Philippine schools. Although no empirical studies have been undertaken to support this view, and many have it, common sense tells us that they are. It is a sad fact that no authoritative overview has ever been presented as to what is really happening in Philippine schools.

What is necessary then is a nationally validated test, or family of tests, that will give entering freshmen maximum assurance of being initially guided in the right direction in attaining their goal. The College Entrance Test is being developed on a national level for such a purpose. At this stage of its development it can be said that some of its validities are comparable to certain American tests, each taken in their own cultural setting, and further studies are being done to improve and establish the usefulness of the test to Filipino students. This paper uses the results of the Gumban and Iledan (1971) study to determine if the regression surfaces obtained from their samples will hold for other samples from different schools.

METHOD

Prediction Schemes

Four prediction schemes were considered in the multiple regression analyses for each of the criterion variables in the Gumban and Iledan (1971) study. These are the following:

1. HSSAA or high school subject area predictor set,
2. CET or College Entrance Test predictor set,
3. HSSAA U CET or the union of HSSAA and CET predictor sets,
4. HS-AVE, CET-OVL or the combination of high school overall average and CET overall score.

Predictor and Criterion Variables

First year first semester college grades were converted from different grading scales to percentages. Averages were obtained on three subject areas, namely: English, Mathematics and Social Science since these were the subjects found to be most common. The overall average for these subjects was also included. The same procedure was used for the high school grades in six subject areas, namely: English, Pilipino, Mathematics, Natural Science, Physical Science, and Social Science. For the CET subtests raw scores were used. An overall score was obtained by weighing the scores on each subtest. Each score was multiplied by the number of items in the corresponding subtest and the sum of the products divided by the total number of items in the battery.

Statistical Procedures

Using the standard partial regression weights obtained in the stepwise multiple linear regression analyses in the Gumban and Iledan (1971) study, thirty-two regression equations were developed, four for each criterion, resulting in sixteen equations for each of the male and female derivation samples. The algebraic procedures in the development of the equations are illustrated in the Appendix. To determine the predictive efficiency of each predictor set outside of the derivation sample school populations the equations were applied on samples obtained from other schools shown in Table 1. It can be seen that these schools vary in certain characteristics among themselves and from the schools from which the derivation samples in the Gumban and Iledan (1971) study were obtained.

RESULTS AND DISCUSSIONS

Predictor Set Suppressors

Tables 2a and 2b are summaries of specific predictor sets in which predictors with negative standard partial regression weights occur. Such predictors or suppressor variables, generally, have zero (or nearly zero) validities and high correlations with the valid predictors in the set. It may be quite difficult for some to comprehend how a variable that has a zero or nearly zero correlation with the criterion can contribute to its predic-

Table 1

Characteristics of Schools from which the Validation Samples Were Obtained.

Validation Sample Code*	Location			Type of Control			Socio-Econ Level***			Size**			No. of Observations	
				Private										
	Region	City	Rural	Sect	Non-Sect	Pub	Low	Mid	High	Small	Med	Large	Male	Female
VSS-01	1	x			x			x			x			23
VSS-02	1	x		x					x		x		15	
VSS-03	2	x				x			x	x			16	39
VSS-04	2	x		x					x			x	19	34
VSS-05	2		x	x				x		x			13	
VSS-06	3	x				x		x				x		23
VSS-07	3		x	x			x				x			19

*Validation Sample Source:
01 – Laguna Colleges
02 – Ateneo de Naga
03 – U.P. in Iloilo
04 – Silliman University
05 – Christ the King
06 – Zamboanga State College
07 – Stella Maris College

**Details of these characteristics are found in the Gumban & Iledan study.

tion. Horst (1941) pointed out that suppressors have a two-fold function, viz., increase criterion validity, and measure and suppress invalid variance in the valid predictors of the set.

To clarify the matter further by an illustration, suppose that $r_{cv} = .35$, $r_{cs} = .00$, and $r_{vs} = .80$ are the zero order correlations between criterion, valid predictor, and suppressor, respectively. As can be readily seen, taken alone, the suppressor is a worthless predictor of the criterion. But solving for $r_{c.vs}$ we have

$$r_{c.vs} = \left[1 - \frac{A}{A_{11}}\right]^{½} = 0.583,$$

where A is the matrix of the zero order correlations and A_{11} a cofactor. Clearly, $r_{c.vs}$ is an improvement over r_{cv}. McNemar (1945), to which interested readers are referred, offers a very simple and elegant discussion on the mode of operation of suppressors basing his argument on set intersection if correlations can be thought of in terms of sets of elements.

The usefulness of a suppressor, however, has to be carefully examined. It may be that its *beta* weight is nearly zero and, thus, will have no effect on the predictive efficiency of the predictor set. Then it can be readily dropped from the set (Duggan and Hazlett, 1963). This can be easily done if it happens to be the last in order of importance among the predictors in the set.

In the r_{cs} column of Table 2a the suppressors HSSAA-PS and CET-Sc have squared validities which are significant at the .01 and .025 level, respectively. Therefore, their inclusion as suppressors in their respective sets is dubious. Lubin pointed out that for a simple two-variable predictor set, such as { HSSAA } in Table 2a, the inequalities

$$r_{vs} > \left[\frac{1}{2} + \frac{r_{cs}}{r_{cv}} - \frac{r_{cs}^2}{2r_{cv}^2}\right]$$

and

$$r_{vs} < \left[\frac{r_{cs}^2}{2r_{cv}^2} + \frac{r_{cs}}{r_{cv}} - \frac{1}{2}\right]$$

must be satisfied, i.e., for HSSAA-PS to be considered a valid suppressor, the first inequality

TABLE 2a

CRITERION AND PREDICTOR VARIABLE INTERCORRELATIONS IN PREDICTOR SETS WITH SUPPRESSORS (MALE DERIVATION SAMPLE).

Predictor Set	Criterion	Valid Predictor	Suppressor	r_{cv}	r_{cs}	r_{vs}
[HSSAA]	COLSAA-E	HSSAA-E	HSSAA-PS	.50	.34	.84
[CET]	COLSAA-E	CET-E	CET-WNR	.36	.01	.27
		CET-Sc		.35		.42
		CET-VA		.35		.40
[HSSAA]	COLSAA-E	HSSAA-E	CET-WNR	.50	.01	.24
U [CET]		CET-E		.36		.27
		CET-M		.28		.48
[HSAA]	COLSAA-SS	HSSA-SS	CET-Sc	.41	.21	.54
U [CET]		CET-M		.35		.62
		CET-E		.31		.54
[HSSAA]	COL-AVE	HSSAA-SS	CET-WNR	.44	.13	.32
U [CET]		CET-M		.44		.48

TABLE 2b

CRITERION AND PREDICTOR VARIABLE INTERCORRELATIONS IN PREDICTOR SETS WITH SUPPRESSORS (FEMALE DERIVATION SAMPLE).

Predictor Set	Criterion	Valid Predictor	Suppressor	r_{cv}	r_{cs}	r_{vs}
[CET]	COLSAA-SS	CET-LR	CET-VA	.28	.09	.37
		CET-E		.26		.48
		CET-M		.25		.45
[HSSAA]	COLSAA-SS	CET-LR	CET-VA	.28	.09	.37*
U [CET]		CET-E	CET-NLS	.26	−.02	.48*
		HSSAA-NS		.21		.21*
		CET-M		.25		.45*
						.16**
						.21**
						.24**
						.41**
						.37***

*correlations between CET-VA and valid predictors
**correlations between CET-NLS and valid predictors
***correlation between the suppressors CET-VA and CET-NLS

must be satisfied, or for it to be considered as another valid predictor, the second inequality must be satisfied. But if the value of r_{VS} is found to be between the two inequalities, i.e.,

$$\left[\frac{r_{cs}^2}{2r_{cv}^2} + \frac{r_{cs}}{r_{cv}} - \tfrac{1}{2}\right] < r_{vs} < \left[\tfrac{1}{2} + \frac{r_{cs}}{r_{cv}} - \frac{r_{cs}^2}{2r_{cv}^2}\right]$$

HSSAA-E should be used by itself as the only valid predictor in the set, which is found to be the case upon substitution of corresponding values from Table 2a; neither of the first two inequalities is satisfied. Therefore, in the final refinement of the regression equation for the set, HSSAA-PS may be excluded although there is some loss in criterion validity. However, the criterion validity of the set, which has now HSSAA-E as its only valid predictor, is still significant beyond the .01 level.

In the predictor set which includes CET-Sc as its suppressor, a more difficult problem for its exclusion is presented. CET-Sc has a moderately high correlation with CET-M, the next valid predictor in order of importance in the set. The absolute value of its beta weight is almost as high as that of CET-M, and it has the highest standard error in the set. This rules out the usefulness of both variables as predictors for COLSAA-SS since they affect only each other's beta weights and not those of the remaining valid predictors. On the other hand, the remaining valid predictors will lose criterion validity to either of the two if both are excluded (Flanagan, et al., 1962). There is no statistical procedure available for the present study for the exclusion of such a "pseudo-suppressor" from a set involving several predictors. This may be a subject for future research. The difficulty of excluding CET-Sc from the set lies in the fact that in the computer analyses the step which includes it as a predictor is a midway step, and in the resulting predictor set it is the third in order of importance, with another following it. Perhaps, one solution is to delete it from the selection set in a subsequent analysis, i.e., for this particular sample, since all of these suppressors may behave differently for other samples from without the derivation sample school population.

Within School Population Predictive Efficiency

Summaries of some of the statistical properties of each of the predictor sets are presented in Tables 3 to 6. Tests of significance (Mijares, 1964) for the coefficients of multiple determination found a few of those with single predictors to be significant well beyond the .025 level and the majority, especially those with multiple predictors, to be significant beyond the .01 level. Except for these significance tests, no mathematical procedure is available wherein these values may be used to prove whether or not the CET can stand on its own merits. All that can be done is to follow usual procedures of comparison with accepted standards, viz., for a test to be *useful* for prediction it must at least have a 20.0 per cent coefficient of determination, between 25.0 to 30.0 per cent to be *good,* and approximately 36.0 per cent for it to be considered among the *better* tests.

Considering the predictor sets of each criterion in the male sample, some are well within the 20.0 and 25.0 to 30.0 per cent categories except for the criterion COLSAA-M. For the three other criteria both {HSSAA} and {CET} contribute equally well as predictors so that a combination of the two results in a better predictor set. In the female sample, however, the {CET} is approximately 65 per cent better than {HSSAA}. A combination of the two makes only for a slightly better predictor set since the contribution of HSSAA is minimal.

On the average {HSSAA} has a forecasting efficiency of 9.4 per cent, {CET} 8.3 per cent, {HSSAA} U {CET} 13.3 per cent, and {HS-AVE, CET-OVL} 12.4 per cent for the male sample. For the female sample the forecasting efficiencies are 2.3 per cent for {HSSAA}, 6.1 per cent for {CET}, 7.9 per cent for {HSSAA} U {CET}, and 6.7 per cent for {HS-AVE, CET-OVL}. These percentages indicate the improvement in prediction with knowledge of the student's high school grades and CET scores over

TABLE 3

PREDICTOR CONTRIBUTION, PREDICTOR SET FORECASTING EFFICIENCY AND COEFFICIENT OF DETERMINATION FOR THE CRITERION COLSAA-M

	MALE				FEMALE			
Predictor Set	Predictor	% Contribution	% $(R^*)^2$	% Efficiency	Predictor	% Contribution	% $(R^*)^2$	% Efficiency
{HSSAA}	HSSAA-M	8.76	8.76	4.5	HSSAA-P	3.80	3.80	2.0
{CET}	CET-M	11.22	11.22	5.8	CET-WNR	7.73	7.73	3.0
{HSSAA} U {CET}	CET-M HSSAA-M	6.40 3.31	12.60	6.6	CET-WNR HSAA-P	7.35 3.42	10.56	5.5
{HA-AVE, CET-OVL}	CET-OVL	8.41	8.41	4.4	CET-OVL HS-AVE	2.37 1.69	4.75	2.4

TABLE 4

PREDICTOR CONTRIBUTION, PREDICTOR SET FORECASTING EFFICIENCY AND COEFFICIENT OF DETERMINATION FOR THE CRITERION COLSAA-E

	MALE				FEMALE			
Predictor Set	Predictor	% Contribution	% $(R^*)^2$	% Efficiency	Predictor	% Contribution	% $(R^*)^2$	% Efficiency
{HSSAA}	HSSAA-E HSSAA-PS	51.41 6.86	25.60	13.8	HSSAA-NS	3.96	3.96	2.0
{CET}	CET-E CET-Sc CET-VA CET-WNR	3.20 5.38 4.41 4.71	17.86	9.2	CET-Sc CET-M	7.08 2.25	13.69	7.0
{HSSAA} U {CET}	HSSAA-E CET-E CET-M CET-WNR	20.16 3.62 3.28 5.29	30.91	16.9	CET-Sc CET-M HSSAA-NS	6.30 1.80 1.06	14.14	7.4
{HS-AVE, CET-OVL}	HS-AVE CET-OVL	12.89 3.20	20.80	11.7	CET-OVL	13.03	13.03	6.8

TABLE 5
PREDICTOR CONTRIBUTION, PREDICTOR SET FORECASTING EFFICIENCY AND COEFFICIENT OF DETERMINATION FOR THE CRITERION COLSAA-SS.

c		MALE			FEMALE			
Predictor Set	Predictor	% Contribution	% $(R^*)^2$	% Efficiency	Predictor	% Contribution	% $(R^*)^2$	% Efficiency
[HSSAA]	HSSAA-SS	16.89	16.89	8.8	HSSAA-NS	4.41	4.41	2.3
[CET]	CET-M CET-E	6.45 3.24	13.18	6.9	CET-LR CET-E CET-M CET-VA	7.90 4.24 3.53 3.96	14.21	7.4
[HSSAA] U [CET]	HSSAA-SS CET-M CET-Sc CET-E	17.89 9.61 9.92 3.69	24.21	12.9	CET-LT CET-E HSSAA-NS CET-M CET-VA CET-NLS	8.29 2.69 2.89 4.93 2.86 2.92	17.39	10.7
[HS-AVE, CET-OVL]	HS-AVE CET-OVL	6.45 4.75	15.05	7.9	CET-OVL HS-AVE	4.45 1.56	7.13	3.7

TABLE 6
PREDICTOR CONTRIBUTION, PREDICTOR SET FORECASTING EFFICIENCY AND COEFFICIENT OF DETERMINATION FOR THE CRITERION COL-AVE.

	MALE				FEMALE			
Predictor Set	Predictor	% Contribution	% $(R^*)^2$	% Efficiency	Predictor	% Contribution	% $(R^*)^2$	% Efficiency
[HSSAA]	HSSAA-SS	19.45	19.45	10.3	HSSAA-P	5.29	5.29	2.7
[CET]	CET-M CET-E	10.89 4.49	21.53	11.4	CET-M CET-WNR CET-E CET-LR	3:06 2.62 1.64 1.25	13.40	7.0
[HSSAA] U [CET]	HSSAA-SS CET-M CET-WNR	13.62 16.13 3.28	30.47	16.7	CET-M HSSAA-P CET-WNR CET-LR	4.58 3.13 2.31 1.85	15.29	8.0
[HS-AVE, CET-OVL]	HS-AVE CET-OVL	9.06 8.64	24.70		CET-OVL HS-AVE	8.82 2.37	13.62	7.1

the knowledge of the criterion mean alone. Although these values seem quite small, where the CET is concerned they still fall within the 4.6 to 40.0 per cent range of usefulness for prediction as set in Guilford's (1965) graph of the functional relationship between correlation coefficients and forecasting efficiencies. It may be stated at this point that these values are true only for these particular samples. Future validation studies will probably show other possibilities.

Due to imperfect correlation predicted grades always tend to regress towards the criterion mean, which results in the non-homoscedasticity of predicted and observed grades such that $\sigma_p < \sigma_c$, i.e., the extent of the deviation of the predicted grades is less than that of the observed criterion. Regression equations, therefore, will predict neither very high nor very low grades which for admissions and/or counseling purposes would be quite adequate, since a student's relative position in his group is not affected by this mathematical phenomenon.

Cross Validation

For clarity, let us first define some terms. The original sample from which regression equations are derived is known as the *derivation* sample. Successive samples on which cross-validation are performed are known as *validation* samples and the correlation between their observed and predicted grades is called *cross-validity.* For purposes of checking the accuracy of prediction the roles of derivation and validation samples may be interchanged and then we have a *double cross-validation.*

A mathematical artifact of cross-validation empirically confirmed by several investigators (Mosier, 1951) is that observed and predicted criterion correlation tend to shrink. Although this is not always the case (Duggan and Hazlett, 1963), i.e., an increase in cross-validity over the estimated population correlation do occur, shrinkage or inflation in cross-validities may be attributed to the differences in criterion-predictor set relation between the derivation and validation samples.

One underlying assumption in cross-validation is that both derivation and validation samples must be comparable and must come from the same school population. On this basis, formulas have been developed which take into consideration shrinkage effect (e.g., Nicholson, 1960; Darlington, 1968) such that the average correlation over several cross-validations is approximately equal to the estimated population correlation. But to cross-validate by using samples from without the derivation sample school population, brings about difficulties which limits the discussion in this study to heuristic interpretations of the resulting cross-validities only as to the general usefulness of the regression equations for the schools from which the validation samples were obtained.

To cross-validate under such conditions presupposes homogeneity between the school populations of the derivation and validation samples. If the regression equations developed from a particular derivation sample are found to be useful for one or several validation samples then the group of schools from which they were obtained can be clustered into subgroups. This will reduce the time and effort for any major validation study which might involve a national sample.

If schools are purely homogeneous, then, the problems of validation are reduced to a minimum. But if they are purely heterogeneous, then, for any one test or set of tests that a group of schools is using a school-to-school validation is implied, which is an expensive and time-consuming undertaking. However, in any group of schools some may have set the same standard of performance and have the same moderator variables that affect the academic success of their students. It is also logical to assume that they will differ or agree in some or all of the dimensions of similar abilities (e.g., Social Science, Mathematics) that they reward. But where homogeneity ends and heterogeneity begins is one mammoth of a problem to be solved.

One limitation of this study is the small sample sizes which grossly affect the estimates of the means and variances of the variables. It was not, therefore, considered meaningful to present a table of their means and standard deviations, since not much confidence can be placed on the differences and equivalences among them. Standard procedures of cross-validation use sample sizes of at least 100 observations.

Another problem is the acceptance of school grades as reliable indicators of achievement since common sense tells us that grading methods vary from school to school and from instructor to instructor, and whether they have been rewarded with total impartiality or not. So taken all together, it is doubtful if a group of samples truly reflect comparable measures of achievement with respect to school grades. But the CET scores, although not entirely error-free, may be taken as more precise measures of the aptitudes and abilities of the students in the validation samples.

The resulting cross-validities in Table 7 cannot be directly compared with the validities of the derivation samples in the Gumban and Iledan

TABLE 7

CROSS-VALIDITIES OF THE VALIDATION SAMPLES

	MALE				FEMALE				
Criterion Predictor Sets	VSS-02	VSS-03	VSS-04	VSS-05	VSS-01	VSS-03	VSS-04	VSS-06	VSS-07
COLSAA-E:									
[HSSAA]	.610**	.156	.399	.083†	.722*	.177	.539*	1.48	.260
[CET]	.331	.692*	.223†	.054†	.747*	.515*	.582*	.651*	.288
[HSSAA] U [CET]	.493	.465	.327	.126†	.835*	.575*	.703*	.598*	.456**
[HS-AVE, CET-OVL]	.422	.690*	.705*	.170†	.856*	.621*	.664*	.673*	.542**
COLSAA-M:									
[HSSAA]	.714*	.009†	.277	.423	.680*	.322	.091	.313	.398
[CET]	.342	.362	.279	.505	.701*	.652*	.250	.356	.276
[HSSAA] U [CET]	.701*	2.33	.375	.589**	.778*	.599*	.363**	.427**	.455
[HS-AVE, CET-OVL]	.763*	.485	.255	.095	.812*	.776*	.469*	.593*	.376
COLSAA-SS:									
[HSSAA]	.851*	.276	.035	.874*	.242	.207	.096	.206	.679*
[CET]	.810*	.359	.189	.642**	.509**	.619*	.664*	.591*	.597*
[HSSAA] U [CET]	.845*	.185	.306	.741*	.335	.680*	.426**	.542*	.669*
[HS-AVE, CET-OVL]	.808*	.579	.017	.858*	.629*	.516*	.709*	.642*	.842*
COL-AVE:									
[HSSAA]	.768*	.444	.095	.726*	.763*	.624*	.325	.291	.553**
[CET]	.681*	.623*	.095	.599**	.808*	.779*	.703*	.735*	.464**
[HSSAA] U [CET]	.809*	.471	.171	.575**	.848*	.764*	.664*	.762*	.439
[HS-AVE, CET-OVL]	.794*	.748*	.487**	.380	.895*	.762*	.768*	.767*	.721*

† uncorrected for bias
*significant at .01 level
**significant at .05 level

study. Some are over- and under-estimates after correction for bias. Nor can these cross-validities be judged on the basis of the .3 minimum value of usefulness for correlation coefficients. Because of the small sample sizes, tests of significance showed values as high as .6 not significant at the .01 level set in the Gumban and Iledan study (1971).

When any set of grades and/or scores, regardless of their source, are used on regression equations of a derivation sample, the resulting predictions will tend to regress towards the criterion mean of that derivation sample. Now if the criterion mean of the validation sample is significantly less (or greater) than the derivation sample criterion mean, then the predictions will be over-estimates (or under-estimates) resulting in great variability and low correlation between the observed and predicted grades of the validation sample. This situation is further confounded by small sample sizes. On the other hand, if the criterion means of both derivation and validation samples are equal or nearly equal, then, the variability between predicted and observed grades becomes minimal due to small sample sizes, so that the resulting cross-validity is high.

The cross-validation results, therefore, poses the following questions. If a cross-validity is significant, does this indicate that the set of predictors for the same criterion in the derivation sample is tapping the same ability in the validation sample? And if it is not, does it mean that the same ability is not being tapped by the right set of predictors? If the significance of the cross-validities is made the basis for indications of usefulness, then, as summarized in Tables 8a and 8b (considering only those that are significant at the .01 level) the equations are useful for some schools. For the male validation sample VSS-02 in Table 8a the regression equations for

TABLE 8a

MALE VALIDATION SAMPLES WITH SIGNIFICANT CRITERION CROSS-VALIDITIES IN FOUR PREDICTOR SETS

Criterion	[HSSAA]	[CET]	[HSSAA] U [CET]	[HS-AVE, CET-OVE]
COLSAA-E		03		03 04
COLSAA-M	02		02	02
COLSAA-SS	02 05	02	02 05	02 05
COL-AVE	02 05	02 03	02	02 ,03

TABLE 8b

FEMALE VALIDATION SAMPLES WITH SIGNIFICANT CRITERION CROSS-VALIDITIES IN FOUR PREDICTOR SETS

Criterion	[HSSAA]	[CET]	[HSSAA] U [CET]	[HS-AVE, CET-OVE]
COLSAA-E	01 04	01 03 04 06	01 03 04 06	01 03 04 06
COLSAA-M	01	01 03	01 03	01 03 04 06
COLSAA-SS	07	03 04 06 07	03 06 07	01 03 04 06 07
COL-AVE	01 03	01 03 04 06	01 03 04 06	01 03 04 06 07

the predictor set { HSSAA } U { CET } seems to be useful in predicting the criteria COLSAA-M, COLSAA-SS and COL-AVE. For VSS-05 it seems to be useful only in predicting COLSAA-SS. The contents of the slots under the other predictor sets may be interpreted in the same manner. As indicated in the Gumban and Iledan study the { CET } predictor set is more predictive for the female sample and the results in this study is fairly indicative of the same trend. As to the degree of usefulness of the regression equations for the validation samples no definite and conclusive findings can be claimed. Estimates of equivalence between validities and cross-validities may be determined if adequate samples are used in future studies.

It is noteworthy that under the { HS-AVE, CET-OVL } predictor set, all the samples appear in one or several of the slots under it despite their absence in some or all of the slots under the three other predictor sets. This may suggest at first that { HS-AVE, CET-OVL } is a better predictor set than the other three. A more plausible explanation, however, is the fact that, since both predictors are linear combinations of their respective subject areas and subtest scores, they contain elements of variables that may be potential predictors for the measures of achievement being rewarded by these schools if regression analysis is done on adequate samples from their respective school populations. Note, for instance, that the female validation sample VSS-01 does not fill the slots of COLSAA-SS under the first three predictor sets but it does under {HS-AVE, CET-OVL}. Possibly this indicates that the criterion COLSAA-SS for this particular school is being tapped by high school and/or CET variables other than those included in the first three predictor sets in the derivation sample.

If a student obtains better grades and scores in variables other than the resulting predictors, the improvements are linearly carried over in the computation of the overall high school average and CET overall score. The temptation, therefore, to consider {HS-AVE, CET-OVL} as the best predictor set is great not only because of the implication in the cross-validity results but because the amount of work in validation will be reduced to a minimum. However, the findings in the Gumban and Iledan study indicated that only the high school variables are homogeneous, while the CET subtests are not. It is only, therefore, possible to consider using the high school overall average in combination with CET subtests scores in future validations that may be undertaken.

In the analysis of the predictor set suppressors two were found to be not useful. This suggests that in future regression analyses, predictor sets with suppressors should be evaluated carefully and a re-analysis done if found necessary.

The coefficients of determination and forecasting efficiencies obtained for each predictor set confirmed the findings of the Gumban and Iledan study that the CET and high school variables are equally predictive for the male derivation sample and, therefore, results in a better predictor set when combined. For the female derivation sample, the CET variables were confirmed to be the better predictors, while the high school variables contributed only minimally.

The cross-validations indicated that the { HSSAA } U { CET } regression equations for the male derivation sample is only generally useful for one of the male validation samples. This is VSS-02 which, if looked up in Table 1, will be found to be similar in characteristics to the derivation sample except for its regional location. The regression equations for the female derivation sample of the same predictor set seems to be generally useful for three female validation samples. A look at Table 1 will show that they vary in some characteristics among themselves and from the derivation sample in the Gumban and Iledan study. This may indicate also that performance in the CET is hardly affected by these characteristics except perhaps where the discrepancies are wide enough such as in socioeconomic status. For the other validation samples the equations seem to be useful only for the prediction of one or two criterion variables.

Cross-validation on a major scale, using adequate samples from different school populations, will hardly settle the question of heterogeneity among Philippine schools, although it may give *some indications* of it, in this study. For instance, if two schools perform equally well on a particular criterion, which in both schools is tapped by different sets of high school and/or CET variables, and other things being equal, are the two schools different? Or are they similar?

If a typology of Philippine schools is envisioned, other multivariate statistical approaches have to be considered to analyze results of continuous researches that may span many years. And although typical aptitude and ability measures as bases for typology are hardly adequate because of the rough clustering that will result, the big pay-off will be in the experience gained in the methodology. Refinements can be done later, considering other quantifiable and measurable variables (e.g., student antecedent factors and personality traits) that contribute to the total make-up of schools as entities where the "sorting processes" that go on in most of them today are still disorganized affairs. So many students are unfairly judged on the basis only of those misleading unidimensional measures we call grades and none of those potentialities which motivate and energize the attainment of excellence in any field of endeavour.

APPENDIX

Development of Regression Equations

The general regression equation is

$$G_p = \sigma_c \left[\sum_{i=1}^{n} \frac{\beta_i}{\sigma_i} X_i - \sum_{i=1}^{n} \frac{\beta_i}{\sigma_i} \bar{X}_i \right] + \bar{X}_c \quad (1)$$

where

G_p = predicted criterion grade,
σ_c = standard deviation of a criterion,
$\bar{X}_c$ = mean of a criterion,
β_i = *beta* weight of a criterion predictor,
$\bar{X}_i$ = mean of a criterion predictor,
X_i = grade or score on a criterion predictor,
n = number of predictors.

Equation (1) may be simplified further to yield

$$G_p = \sum_{i=1}^{n} b_i X_i \pm C \quad (2)$$

where

$$b_i = \frac{\sigma < \beta_i}{\sigma_i} \quad (3)$$

and

$$C = \bar{X}_c - \sigma_c \sum_{i=1} \frac{\beta_i}{\sigma_i} X_i \quad (4)$$

Equation (3) is the b weight for a particular predictor and equation (4) the constant for a particular equation. Depending on the grading scale used for the criterion, C may be positive or negative. If $\bar{X}_c$ is in per cent, raw score or T-score C is usually positive, since

$$\bar{X}_c > \sum_{i=1}^{n} \frac{\beta_i}{\sigma_i} \bar{X}_i .$$

If $\bar{X}_c$ is in GPA, e.g., 1.0, 1.5, it may happen that

$$\bar{X}_c < \sum_{i=1}^{n} \frac{\beta_i}{\sigma_i} \bar{X}_i$$

and the resulting C will be negative. The function of C in the regression equation is to ensure that the estimated mean of the predicted grades will be equal to the mean of the observed grades.

In developing regression equations, equations (2) and (4) are expanded depending on the number of predictors for a particular criterion. For a two-predictor set the expansion of the general equation is

$$G_p = b_1 X_1 + b_2 X_2 \pm C,$$

where

$$C = \bar{X}_c - \sigma_c \left[\frac{\beta_1}{\sigma_1} X_1 + \frac{\beta_2}{\sigma_2} X_2 \right]$$

$$b_1 = \frac{\sigma_c \beta_1}{\sigma_1} \quad \text{and} \quad b_2 = \frac{\sigma_c \beta_2}{\sigma_2}$$

Using data from the Gumban and Iledan study on the HSSAA predictor set of the male sample with COLSAA-E as the criterion,

$$b_1 = \frac{5.18 \times 0.717}{4.36} = 0.852,$$

$$b_2 = \frac{5.18 \times (-0.262)}{5.34} = -0.254,$$

and

$$C = 84.79 - 5.18 \left[\frac{0.717 \times 86.69}{4.36} + \frac{-0.262 \times 86.15}{5.34} \right],$$

$$= 32.838.$$

Replacing b_1, b_2 and C in the equation,

$$G_p = 0.852X_1 - 0.254X_2 + 32.8382$$

where

X_1 = average grade in HSSAA-E,

and

X_2 = average grade in HSSAA-PS.

All that is necessary to obtain the first semester predicted criterion grade of a particular student is to substitute in the equation his grades in the above subject areas.

The development of regression equations although simple enough is quite cumbersome especially if a number of predictors are involved. The use of a table computer will be of much help. Tables A-1 to A-4 and B-1 to B-4 are the summaries of the regression equations for the four prediction schemes. Tables A-5 and B-5 are examples of predicted games.

For admissions and/or guidance purposes, however, using regression equations for prediction when thousands of students are involved is a time-consuming work. A more practical solution is to generate an expectancy table using regression equations.

TABLE A-1

REGRESSION EQUATIONS OF FOUR PREDICTOR SETS FOR THE CRITERION COLSAA-E (MALE SAMPLE)

Predictor Set	Predictors	Regression Equations
[HSSAA]	X_1 = grade in HSSAA-E X_2 = grade in HSSAA-PS	$G_p = 0.8518X_1 - 0.2541X_2 + 32.8382$
[CET]	X_1 = score in CET-E X_2 = score in CET-Sc X_3 = score in CET-WNR X_4 = score in CET-VA	$G_p = 0.2667X_1 + 0.1561X_2 - 0.2721X_3 + 0.2740X_4 + 66.4686$
[HSSAA] U [CET]	X_1 = grade in HSSAA-E X_2 = score in CET-E X_3 = score in CET-WNR X_4 = score in CET-VA	$G_p = 0.5334X_1 + 0.2868X_2 - 0.2906X_3 + 0.2056X_4 + 27.9485$
[HS-AVE, CET-OVL]	X_1 = high school overall average X_2 = CET overall score	$G_p = 0.4217X_1 + 0.2568X_2 + 40.5801$

TABLE A-2

REGRESSION EQUATIONS OF FOUR PREDICTOR SETS FOR THE CRITERION COLSAA-M (MALE SAMPLE)

Predictor Set	Predictors	Regression Equations
[HSSAA]	X_1 = grade in HSSAA-M	$G_p = 0.2845X_1 + 57.8193$
[CET]	X_2 = score in CET-M	$G_p = 0.3805X_1 + 73.1166$
[HSSAA] U [CET]	X_1 = score in CET-M X_2 = grade in HSSAA-M	$G_p = 0.2431X_1 + 0.1749X_2 + 61.3855$
[HS-AVE, [CET-OVL]	X_1 = CET overall score	$G_p = 0.6627X_1 + 62.1261$

TABLE A-3

REGRESSION EQUATIONS OF FOUR PREDICTOR SETS FOR THE CRITERION COLSAA-SS (MALE SAMPLE)

Predictor Set	Predictors	Regression Equations
[HSSAA]	X_1 = grade in HSSAA-SS	$G_p = 0.4901X_1 + 39.4157$
[CET]	X_1 = score in CET-M X_2 = score in CET-E	$G_p = 0.3314X_1 + 0.3104X_2 + 62.1489$
[HSSAA] U [CET]	X_1 = grade in HSSAA-SS X_2 = score in CET-M X_3 = score in CET-Sc X_4 = score in CET-E	$G_p = 0.5044X_1 + 0.4045X_2 - 0.2453X_3 + 0.3311X_4 + 27.2947$
[HS-AVE, CET-OVL]	X_1 = high school overall average X_2 = CET overall score	$G_p = 0.3427X_1 + 0.3593X_2 + 41.6327$

TABLE A-4

REGRESSION EQUATIONS OF FOUR PREDICTOR SETS FOR THE CRITERION COL-AVE (MALE SAMPLE)

Predictor Set	Predictors	Regression Equations
[HSSAA]	X_1 = grade in HSSAA-SS	$G_p = 0.4216X_1 + 46.3193$
[CET]	X_1 = score in CET-M X_2 = score in CET-E	$G_p = 0.3452X_1 + 0.2931X_2 + 63.4174$
[HSSAA] U [CET]	X_1 = grade in HSSAA-SS X_2 = score in CET-M X_3 = score in CET-WNR	$G_p = 0.3527X_1 + 0.4278X_2 - 0.1873X_3 + 45.5287$
[HS-AVE, CET-OVL]	X_1 = high school overall average X_2 = CET overall score	$G_p = 0.3256X_1 + 0.3885X_2 + 43.1534$

TABLE A-5
EXAMPLES OF PREDICTED CRITERION GRADES USING THE REGRESSION EQUATION FOR THE HSSAA U CET PREDICTOR SET (MALE SAMPLE)

Grades and Score on Predictor Variables								Observed and Predicted Criterion Grades							
HSSAA				CET				COLSAA E		COLSAA M		COLSAA SS		COL AVE	
x E	SS	PS	M	WNR	M	E	Sc	X_c	G_p	X_c	G_p	X_c	G_p	X_c	G_p
85	87	87	87	17	20	39	54	85	84	80	81	80	79	82	82
89	87	80	82	22	27	45	50	88	87	76	82	85	85	83	84
86	86	89	89	17	28	40	46	88	86	90	84	85	84	88	85
82	83	83	81	22	31	41	52	80	83	90	83	85	83	85	84
88	89	85	85	19	23	38	42	83	85	90	82	90	84	88	83
90	89	86	90	16	24	39	52	85	87	90	83	85	82	87	84
80	82	79	81	18	17	33	39	80	78	80	80	72	77	77	78
89	87	93	90	13	24	41	52	81	88	85	83	85	82	84	84
91	97	97	92	24	26	42	57	93	87	96	84	96	87	95	86
89	88	90	91	20	28	42	53	85	87	72	84	80	84	79	85
87	87	90	88	21	25	37	46	88	84	90	83	85	82	88	83
87	90	81	86	18	27	36	55	81	85	76	83	90	82	82	85
82	83	84	87	19	24	36	32	81	81	90	82	76	83	82	82
85	84	84	82	17	22	40	49	81	84	72	81	85	80	79	81
86	87	88	84	11	17	35	48	83	84	76	80	76	78	78	81
88	89	86	83	16	29	43	53	90	89	80	83	90	85	87	86
89	89	88	91	18	27	33	42	85	85	72	84	76	84	78	85
92	90	92	88	15	16	39	34	80	87	76	81	85	84	80	81
95	97	97	88	21	28	44	52	93	91	85	84	76	89	85	88
81	79	79	76	9	15	32	31	93	81	80	78	80	76	84	78

TABLE B-1
REGRESSION EQUATIONS OF FOUR PREDICTOR SETS FOR THE CRITERION COLSAA-M (FEMALE SAMPLE)

Predictor Set	Predictors	Regression Equations
[HSSAA]	X_1 = grade in HSSAA-NS	$G_p = 0.1711X_1 + 68.9144$
[CET]	X_1 = score in CET-Sc X_2 = score in CET-M	$G_p = 0.1376X_1 + 0.1146X_2 + 77.10$
[HSSAA] U [CET]	X_1 = score in CET-Sc X_2 = score in CET-M X_3 = grade in HSSAA-NS	$G_p = 0.1299X_1 + 0.1023X_2 + 0.0886X_3 + 68.315$
[HS-AVE, CET-OVL]	X_1 = CET overall score	$G_p = 0.3687X_1 + 72.99$

TABLE B-2

REGRESSION EQUATIONS OF FOUR PREDICTOR SETS FOR THE CRITERION COLSAA-M (FEMALE SAMPLE)

Predictor Set	Predictors	Regression Equations
[HSSAA]	X_1 = grade in HSSAA-P	$G_p = 0.2097X_1 + 65.7160$
[CET]	X_1 = score in CET-WNR	$G_p = 0.3153X_1 + 77.7474$
[HSSAA] U [CET]	X_1 = score in CET-WNR X_2 = grade in HSSAA-P	$G_p = 0.3073X_1 + 0.1989X_2 + 60.9976$
[HS-AVE, CET-OVL]	X_1 = CET overall score X_2 = high school overall average	$G_p = 0.2722X_1 + 0.2143X_2 + 54.9980$

TABLE B-3

REGRESSION EQUATIONS OF FOUR PREDICTOR SETS FOR THE CRITERION COLSAA-SS (FEMALE SAMPLE)

Predictor Set	Predictors	Regression Equations
[HSSAA]	X_1 = grade in HSSAA-NS	$G_p = 0.2875X_1 + 60.6807$
[CET]	X_1 = score in CET-LR X_2 = score in CET-E X_3 = score in CET-VA X_4 = score in CET-M	$G_p = 0.4136X_1 + 0.3003X_2 - 0.2706X_3 + 0.2286X_4 + 67.2168$
[HSSAA] U	X_1 = score in CET-LR X_2 = score in CET-E X_3 = grade in HSSAA-NS X_4 = score in CET-VA X_5 = score in CET-M X_6 = score in CET-NLS	$G_p = 0.4239X_1 + 0.2391X_2 + 0.2327X_3 - 0.2298X_4 + 0.2699X_5 - 0.2368X_6 + 54.1282$
[HS-AVE, CET-OVL]	X_1 = CET overall score X_2 = high school overall average	$G_p = 0.3430X_1 + 0.1895X_2 + 59.1686$

TABLE B-4

REGRESSION EQUATIONS OF FOUR PREDICTOR SETS FOR THE CRITERION COL-AVE (FEMALE SAMPLE)

Predictor Set	Predictors	Regression Equations
[HSSAA]	X_1 = grade in HSSAA-P	$G_p = 0.2057X_1 + 65.3279$
[CET]	X_1 = score in CET-M X_2 = Score in CET-WNR X_3 = score in CET-E X_4 = score in CET-LR	$G_p = 0.1428X_1 + 0.1644X_2 + 0.1252X_3 + 0.1106X_4 + 70.4608$
[HSSAA] U [CET]	X_1 = score in CET-M X_2 = grade in HSSAA-P X_3 = score in CET-WNR X_4 = score in CET-LR	$G_p = 0.1746X_1 + 0.1703X_2 + 0.1542X_3 + 0.1343X_4 + 59.8640$
[HS-AVE, CET-OVL]	X_1 = CET overall score X_2 = high school overall average	$G_p = 0.3240X_1 + 0.1567X_2 + 60.4603$

TABLE B-5

EXAMPLES OF PREDICTED CRITERION GRADES USING THE REGRESSION EQUATIONS FOR THE HSSAA U CET PREDICTOR SET (FEMALE SAMPLE)

Grades and Scores on Predictor Variables									Observed and Predicted Criterion Grades							
HSSAA		CET							COLSAA E		COLSAA M		COLSAA SS		COL AVE	
P	NS	W NR	VA	NLS	LR	E	M	Sc	X_c	G_p	X_c	G_p	X_c	G_p	X_c	G_p
84	80	19	17	16	19	39	23	42	83	83	85	84	87	89	85	84
81	80	19	17	15	17	41	26	46	85	84	82	83	90	89	85	83
83	81	17	14	11	12	37	17	32	78	81	80	83	90	86	82	81
86	81	13	24	20	19	39	25	51	88	85	87	82	90	87	88	83
86	79	16	19	21	17	35	19	39	82	82	76	83	78	82	79	81
91	81	20	13	10	11	30	13	17	85	79	82	85	80	83	82	82
83	79	23	13	13	17	20	9	28	79	80	75	85	76	81	76	81
88	87	14	22	13	14	39	21	40	84	83	87	83	87	87	86	83
86	88	21	21	17	21	43	26	52	90	86	75	85	92	92	86	85
87	86	13	18	10	19	38	19	48	84	84	72	82	87	90	81	83
93	90	25	26	25	19	42	27	56	87	86	72	87	81	89	80	87
78	80	13	16	11	10	38	22	43	81	83	72	81	78	86	77	80
85	84	11	11	8	11	14	14	31	81	81	72	81	81	81	78	81
88	84	21	22	19	18	36	16	55	84	85	81	85	90	85	85	83
95	93	25	28	23	21	44	29	58	90	87	96	88	96	91	94	88
79	73	21	21	17	11	40	23	43	77	83	90	83	75	83	80	82
83	87	18	13	21	10	25	12	19	77	80	81	83	87	80	81	80
85	77	18	21	14	14	41	17	44	81	83	84	83	87	84	84	82
88	83	18	20	13	13	37	20	47	90	84	84	84	84	86	86	83
77	82	22	24	20	19	38	27	50	87	85	90	83	84	87	87	84

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