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R. GENE HOFFMAN

Research Report No. 21

April, 1979

This research was partially supported by the Personnel and Training Research Programs, Psychological Sciences Division, Office of Naval Research under Contract No. N00014-75-C-0884, Contract Authority Identification Number NR 151-375, Benjamin Schneider and C. J. Bartlett, Principal Investigators.

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Student ability, involvement in the class, and classroom climate created by the instructor activities were examined as multiple and interactive predictors of course performance for 915 students in 74 sections of a mathematics course. Climate was defined in two ways: (1) as individual perceptions and (2) as shared perceptions. Two parallel analyses were conducted using the two definitions of climate. Each analysis resulted in ability, involvement and climate contributing unique variance in the prediction of student

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examination performance on a common exam. Climate dimensions contributing to performance were coordination of class activities, instructor skill, and the extent of critical demands (a negative relationship). The most significant difference between the two analyses was the appearance of a significant ability X coordination interaction in the analysis using shared climate perceptions. This difference was interpreted to be a result of a confounding of the interaction in the individual perceptions of coordination. The relationship between the interaction and predictive accuracy was explored.

ABILITY, INVOLVEMENT AND CLIMATE
AS MULTIPLE AND INTERACTIVE PREDICTORS OF PERFORMANCE

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For a number of years, researchers have recognized the potential impact of the joint effects of individual differences and situational differences on individual task performance. Following Cronbach's (1957) directive to look for aptitude/treatment interactions, research in education has ballooned to an almost incomprehensible collection of studies examining such interactions (Cronbach & Snow, Note 1). Organizational psychology has also been bitten by the person/situation call to order. There have been numerous attempts to understand the interactions between individual differences and situational differences as they relate to performance, particularly in the field of leadership (Kerr, Schriescheim, Murphy & Stodgill, 1974), climate, (Hellriegel & Slocum, 1974), and in motivation (e.g., Hackman & Oldham, 1975). The excitement over person/situation interactions has been predicated on the belief that the interaction contains the greatest source of understanding (Atkinson, 1974) and predictive accuracy (Dunnette, 1963).

A number of issues can be raised about the exclusive focus on the interaction as the primary source of understanding. These include (1) the frequent failure to analyze both regression coefficients and correlation coefficients as related but not identical descriptions of the person/performance relationship (Cronbach & Snow, Note 1), (2) the failure to consider mean differences in performance, in addition to relationship differences, which may be created by situational differences (Schneider, 1978a) and (3) problems centering on the measurement of situational differences (Schneider, 1975; Schneider & Snyder, 1975).

With respect to the first issue, Cronbach and Snow (Note 1) and Cohen and Cohen (1975), among others, indicate that, in the strictest sense, an interaction is conceptualized as a relationship between two variables that is conditional on the value of a third variable, and that the relationship difference appears in the regression slope. Thus, differences in correlation coefficients for subgroups may or may not be accompanied by an interaction, depending on the variance in the predictor and criterion variables. Conversely, an interaction, i.e., difference in slopes, is not necessarily indicative of a difference in predictive accuracy as defined by the correlation coefficient.

To complicate matters further, a significant difference between correlation coefficients indicates predictive accuracy within each subgroup (i.e., one minus the sum of the residuals squared divided by performance variance for the subgroup). Since the performance measure is identical for each subgroup, one could also directly compare errors of prediction between subgroups. It is possible to find differences in correlations between two subgroups in which errors of prediction (i.e., sum of residuals squared) were identical for the subgroups. Similarly, one might find a significant interaction (i.e., slope differences) accompanied by correlational differences (differential validity), but with the same errors of prediction. Thus, regression slopes, correlation coefficients, and average squared residual scores all provide related but separate pieces of information, each suggesting a somewhat different perspective for examining person/situation joint effects.

A second issue concerning the interpretation of situation effects on the person-performance relationship concerns group mean differences on the performance criteria that may be created by situational differences. Kerlinger and Pedhazur (1973) recommend that when an interaction is found, it is not necessary to test for main effects. Their suggestion seems consistent with the very definition of an interaction -- that the main effect of a variable is not constant over the values of some third variable. On the other hand, information is lost if only regression and/or correlation coefficients are examined. For example, knowing only that the ability-performance relationship is stronger in a consistent climate (e.g., innovative and close supervision), as shown by Frederiksen (Note 2) gives no indication as to which situation, consistent or inconsistent, had the best overall level of performance. Fiedler's (1971) research on leadership, for example, has been criticized on precisely this point (Landy & Trumbo, 1976).

The importance of this issue becomes obvious when it is realized that two competing assumptions about the effects of situations on ability-performance relationships exist. In the field of industrial/organizational psychology, it has been suggested that situations be structured to maximize the ability-performance relationship (Schneider, 1975; 1978a) in order to maximize individual potential and therefore to maximize the collective output. In fact, it has even been suggested that the ability-performance relationship be used as a sign of organizational health.

On the other hand, one gains the opposite implication from the educational literature. For example, Cronbach and Snow (Note 1) hypothesize that a low correlation between pre-test and post-test scores indicates that the instructor has overcome student deficiencies. For these latter scholars, situations which exhibit low regression/slopes are expected to show the highest overall criterion performance.

Thus, one may not want to presume whether overall criterion performance is higher or lower for situations which have high person/performance relationships. Note that the answer to this issue does not lie in looking at intercept differences (Kerlinger & Pedhazur, 1973). Since the regression lines for each situation are not parallel and the range of predictor scores may lie some distance from the y-axis, the differences in the y-intercept may be totally misleading. Therefore, examination of subgroup performance means seems to be the straightforward solution.

Another issue concerning person/situation interactions concerns the measurement of situations, particularly in correlational studies where situational differences are assessed by participant judgments. It has been suggested (Schneider, 1978b) that the person/situation interaction may be confounded in the measurement of the situation. That is, reports by an individual of the situation are an amalgam of both individual and situational differences which may contain interaction information. Attempts to find a statistical interaction between these reports and individual characteristics may be a redundancy that would fail (Schneider, 1978b). This argument is similar to the criticism Mobley and Locke (1970) made of attempts to weight job facet satisfaction responses by importance. A person/situation interaction may conceptually be present but statistically confounded at the individual level of analysis. However, if Schneider's (1975) prescriptions for assessing situational conditions as an aggregate of the perceptions of individuals is followed, then the collective data should be less systematically contaminated by individual differences and therefore more likely to exhibit person/situation interactive effects.

The use of interactions has helped our understanding beyond that possible with the bivariate approach. For example, some of the confusion in leadership research has been clarified by using contingency models (Kerr, et al., 1974; House & Mitchell, 1974) which highlight the significance of situational moderators (some of which are follower characteristics) of the relationship between leadership characteristics and some criterion of leadership effectiveness. On the other hand, Cronbach's (1975) analysis of educational research finds that the simple person/situation (i.e., educational treatment) interaction is difficult to find because it seems to be masked by higher order interactions. Note that in the research reviews by Cronbach, situational differences were most often gross qualitative treatment differences, while the leadership literature most often focuses on variance on one dimension of the situation (e.g., task ambiguity or some aspect of climate). This difference in focus suggests the possibility that person/situation interactions in situations that are multidimensional may be unstable and difficult to find because of variance within similarly defined situations. For example, Jackson (1962) has suggested that it is narrow-minded to view all teaching alike; that teacher characteristics within similar methods may have influence on the relationship between students' ability and their performance. Such within method effects may cloud any interactions between difference methods and the ability/performance relationship.

The focus of this research is on instructor behaviors as an influence on student performance directly and on the relationship between student ability and performance. Instructor behavior can be conceptualized as a situational variable much the same way as leadership or managerial style has been used as a climate variable (Hellreigel & Slocum, 1974). In light of the above discussion, the present research examines the effects of instructor behavior as perceived by each individual and also as aggregated at the group (i.e., class) level. Moderated multiple regression in which interaction information "is carried by" (Cohen & Cohen, 1975), a product term will be used to examine slope differences as a function of teacher style. If interactions are found, teachers with similar style on the relevant teacher dimension will be subgrouped so that mean differences in student performance, differences in prediction errors between subgroups, and differences between subgroup correlations can be examined in relation to teacher style.

METHOD

Subjects and Procedure

Students in 75 sections of an introductory methematics course completed a faculty evaluation questionnaire. The questionnaire was modified to ask students to provide their student identification numbers and SAT Math scores. The questionnaire indicated that the student numbers were for research purposes only and would not be given to the instructor. Such instructions appear to reduce the potential bias associated with the identification process (Sharon & Bartlett, 1969). The student numbers were necessary to match student questionnaire responses to course performance.

Students who did not provide their student numbers were not used in the analysis. This reduced the sample from 1213 students to 915 students and eliminated one entire section. The mean, across all sections, of the average within section examination score (all students included) was 72.65, compared to a mean of 75.33 for the students that responded to the questionnaire and provided their student numbers. This suggests that the sample used in this analysis tended to exclude the lower performing students. However, the fact that one entire section refused to provide their student numbers suggests that something other than performance level influenced the decision not to identify themselves. Average performance for that class was above the average performance of the other classes; it was, however, within one standard deviation.

Variables

Instructional style was assessed by four scales of the Check-List of Instructional Characteristics (CLIC; Hoffman, 1976). These indluced (1) Knowledge and Skill, indicating the instructor's knowledge, organization and clarity, (e.g., "explained how topics in the course were related to each other"). (2) Consideration, which describes instructor activities which facilitate interaction ("asked students questions"), (3) Critical Demands, which indicates the instructor's strictness with students ("criticized students in front of others"), and (4) Coordination, which describes the degree to which class presentation, readings and examination were integrated by the instructor ("examination questions could be anticipated"). When averaged across students within each class, these scales provide an index of students' "shared perceptions" (Schneider, 1975) of the classroom "climate." They were also treated as individual variables representing individual perceptions.

One additional CLIC scale was also included in the analysis. It describes Student Involvement in the course and therefore was treated as an individual differences variable and not a class differences variable. Conceptualized as a situation specific variable, Student Involvement was examined both as an independent variable for performance and as mediator of the course climate.

Estimates of student SAT Math scores were obtained on the faculty evaluation questionnaire by asking students to indicate which of five score intervals contained their SAT Math score. Intervals were constructed such that the middle interval obtained the mean freshman SAT Math Score.

Student performance was assessed by five course examinations. The examinations were identical for all class sections. Individual student performance was calculated as the mean of their five examination scores.

Analysis

Two parallel regression analyses were conducted. Each was conducted at the individual level of analysis with individual class performance as the criterion and individual student ability and individual Student Involvement as individual differences (person) variables. The difference between the analyses was in the definition of the situational variables. For the individual analysis, students' individual perceptions of the instructor were used. For the climate analysis, each student was assigned his or her section average rating for the four CLIC (situation) variables.

In each analysis, modified hierarchial multiple regression was used with ability entered first, then the climate variables were entered, retaining only those with significant beta weights. Then, Student Involvement was entered and any non-significant climate variables were dropped. Student Involvement was entered after climate on the assumption that part of the variance in Student Involvement is a function of class climate, so that adding Student Involvement before climate would underestimate the effect of climate.

Person/situation interactions were examined via the added contribution of the eight products of the two person variables each times the four situation variables. For the individual analysis, individual perceptions were used, while for the climate analysis shared perceptions were used.

Missing data was handled by pair-wise deletion during computation of correlations. Multiple regression significance tests were based on the lowest N in the correlation matrix (n=794).

RESULTS

Means, stands deviations, reliability estimates and N's for each variable are presented in Table 1. For the individual variables, internal consistency reliabilities are based on Spearman-Brown estimates based on the average intercorrelation of items on each scale. The performance reliability estimate is based on the Spearman-Brown corrected average intercorrelation of the five examinations. For the climate variables, interrater reliabilities were estimated by an odd-even split of students within each class computing the correlation between halves across all class sections and correcting the correlations by the Spearman-Brown formula. These various estimates of reliability indicate that with the exception of the climate variable called Coordination all reach clearly acceptable levels.

Table 1

Means Standard Deviations, and Reliability Estimates

for Individual and Climate Variables

Variables	$\overline{X}$	σ	N	r_{tt}[a]
Individual				
Knowledge and Skill	3.89	.67	915	.86
Consideration	3.56	.80	915	.82
Critical Demands	1.92	.60	914	.72
Coordination	3.18	.70	912	.74
Student Involvement	3.50	.63	908	.74
SAT Math	3.16	.81	794	-
Average Test Performance	75.33	13.74	915	.87
Climate				
Knowledge and Skill	3.89	.32	915	.77
Consideration	3.56	.49	915	.90
Critical Demands	1.94	.29	915	.84
Coordination	3.16	.20	915	.19

[a] See text for description of reliability estimates.

Intercorrelations between variables are presented in Table 2. The best single predictor of performance is the individual variable Student Involvement (r = .38), followed by SAT Math (r = .33). Shared climate correlations with individual performance were in the range of .07 to .15 (absolute values), while individual perceptions of climate ranged from .14 to .21 (again, absolute values).

Individual Analysis

Variables included in this analysis were: student performance as the criterion; student ability and individual climate perceptions as hypothetical determinants of performance; and Student Involvement as both a determinant of performance and a mediator of climate.

Table 3 presents the regression results. As indicated above, ability correlated .33 with performance, representing 10.9% of the variance in performance. With ability accounted for, all four individual climate perceptions were significantly (p <.01) related to performance. For Knowledge and Skill, Consideration, Critical Demands, and Coordination, respectively, partial correlations were .17, .20, -.13 and .17. Using the regression procedure, three of those four scales entered and remained in the regression equation with significant beta weights. These were Consideration, Critical Demands and Coordination. Together, these three scales added 6% to the variance accounted for in performance.

Student Involvement was then entered into the equation and it had a significant weight (p <.01) but the contribution of Consideration became non-significant and, therefore, was dropped from the equation. Ability, the two remaining climate perceptions (Critical Demands and Coordination) and Student Involvement accounted for 25% of the variance in student performance.

Table 2

Correlations Among Individual, Climate and Performance Variables

Variables	Climate 2	3	4	Individual 5	6	7	8	9	10	11
Climate										
1. Knowledge and Skill	.78	-.43	.30	.45	.45	-.16	.09	.15	-.01	.14
2. Consideration		.42	.13	.35	.60	-.18	.03	.15	-.04	.12
3. Critical Demands			-.20	-.20	-.25	.47	-.02	-.04	-.02	-.07
4. Coordination				.13	.07	-.02	.28	.10	.04	.14
Individual										
5. Knowledge and Skill					.62	-.24	.27	.30	.03	.17
6. Consideration						-.26	.19	.32	.05	.21
7. Critical Demands							-.07	-.06	-.04	-.14
8. Coordination								.24	.16	.21
9. Student Involvement									-.07	.38
10. SAT Math										.33
11. Performance										

NOTE: Correlations greater than .07, $p < .05$; correlations greater than .09, $p < .01$; correlations greater than .12, $p < .001$.

Table 3

Regression Analyses of Ability, Student Involvement and Individual Perceptions of Climate as Predictors of Student Performance

Predictor Variables Included	R	R^2	F	Standardized Regression Weights: Ability	Consideration	Critical Demands	Coordination	Student Involvement
Ability	.33	.109	97.02	.33				
Ability/ Climate	.41	.169	40.17	.30	.15	-.08	.13	
Ability/ Climate/ Student Involvement	.50	.251	66.05	.29		-.10	.08	.33
Ability/ Student Involvement	.48	.234	120.56	.30				.35

Student Involvement was then entered nto the equation and it had a significant weight ($p < .01$) but the contribution of Consideration became non-significant and, therefore, was dropped from the equation. Ability, the two remaining climate perceptions (Critical Demands and Coordination) and Student Involvement accounted for 25% of the variance in student performance.

As a result of Consideration being dropped from the regression equation, there are two possible ways to look at the variance accounted for by the addition of Student Involvement. One way would be to determine the variance that Student Involvement adds to the final equation, i.e., the amount that Student Involvement adds to ability and the two climate perceptions. However, because in some sense Student Involvement replaced Consideration, perhaps a more meaningful estimate of the unique variance contributed by Student Involvement is to compare the equation containing Consideration to the other two climate perceptions and ability. In that way, the performance variance shared by Consideration and Student Involvement is attributed to Consideration not Student Involvement. Thus, a comparison of the ability, climate and Student Involvement model to the ability plus climate model indicates that Student Involvement uniquely accounts for 8.2% of the variance in performance, at least for this system of variables.[1]

Alternatively, one could argue that instructor activities and, concomitantly, student perceptions of those activities are in part a reaction

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[1]Other assessments of the class climate could reduce the apparent impact of Student Involvement. That is, Student Involvement may mediate other unmeasured aspects of classroom climate.

to Student Involvement (cf. Greene, 1975). That is, some amount of the variance in the climate perception may be determined by Student Involvement, and vice versa. If this is the case, the performance variance which may be attributed to Student Involvement would be greater than the 8.2% derived above. Under such a condition of reciprocal relationships, it is not possible to state precisely how much of the performance variance accounted for should be attributed to Student Involvement. However, one can bracket that amount with upper and lower bound estimates. The 8.2% defines the lower bound estimate for this system of variables (see footnote 1). An upper bound estimate can be derived by determining the contribution that Student Involvement adds to ability alone. The last line of Table 3 shows that Student Involvement and ability combine to account for 23.4% of the variance in performance. Thus, Student Involvement adds 12.5% to ability, so 12.5% can be taken as the upper bound of the Student Involvement contribution.

Similarly, upper and lower bounds can be derived for the contribution of the climate perceptions. The upper bound is the 6% which the three climate variables add to ability. The lower bound is derived from comparing the ability/climate/Student Involvement model to the ability/Student Involvement model. Thus, the 1.7% which climate adds to ability and Student Involvement is the lower bound estimate of the impact of climate on performance.

Finally, for the analysis using individual perceptions of class climate, no person/situation interactions were significant.

Another way to phrase these results is that the unique variance associated with climate is 1.7%, and the common variance in performance shared by Student Involvement and climate is 4.3%. Finally, for simplicity, ability is assumed to have only a direct relationship (e.g., it does not mediate Student Involvement or climate) and it accounts for 10.9% of the variance in performance. Thus, the total variance accounted for in student performance using only individual level variables is 25.1%.

Climate Analysis

The climate analysis parallels the individual analysis except shared class perceptions (average within-class individual perceptions) were used as climate indices. Table 4 presents the climate regression analyses for student performance.

With ability held constant, all four climate measures were significantly related to student performance. The partial correclations were .15, .14, .13 (all *p* <.01) and -.07 (*p* <.05) for Knowledge and Skill, Consideration, Coordination and Critical Demands, respectively. Only two of the climate measures entered and remained in the regression solution after ability was entered; Knowledge and Skill, and Coordination. Combined, they increased the variance accounted for in performance by 2.9% (R = .37).

Student Involvement was entered into the regression equation, adding 10.9% to the variance accounted for (*p* <.01). Both Knowledge and Skill, and Coordination remained in the regression equation with significant regression weights (*p* <.01).

Analogous to the individual analysis, upper and lower bounds of the linear contribution of Student Involvement and Climate were determined. The lower bound of Student Involvement is the 10.9% indicated above. The upper bound of Student Involvement was derived in the individual analysis as 12.5% (i.e., increase of Student Involvement over ability). The lower bound of climate is the difference between the ability/Student Involvement/

Table 4

Regression Analyses of Shared Climate Perceptions, Individual Ability and Student Involvement as Predictors of Student Performance

Predictor Variables Included	R	R^2	F	Standardized Regression Weights: Ability	Knowledge and Skill	Coordination	Student Involvement
Ability	.33	.109	97.02	.33			
Ability/ Climate	.37	.138	42.07	.33	.12	.09	
Ability/ Climate/ Student Involvement	.50	.247	64.62	.30	.07	.07	.34
Ability/ Student Involvement	.48	.234	120.56	.30			.35
Ability/ Climate' Student Involvement/ Interaction	.51	.265	56.73	$(.32 + .14\ Z_{coor})$	.08	.07	.34

climate model and the ability/Student Involvement model. That difference is 1.3%. The upper bound is the 2.9% described above. In other words, the unique linear contribution of Student Involvement is 10.9%, the unique linear contribution of climate is 1.3% and the shared contribution is 1.6%.

In addition to these main effects, a significant (p <.01) interaction was found between Coordination and Student ability. Inclusion of the Coordination times ability product term increases the performance variance accounted for by 1.8%, increasing the multiple correlation to .51 (see the last row in Table 4).

Since an interaction indicates that the effect of the first variable is a function of the second and vice versa, the contribution of the interaction may best be interpreted as shared variance accounted for in performance. Thus, the above accounting system is revised such that the total shared variance is 3.4%. That shared variance now represents both mediated relationships (climate through Student Involvement and/or Student Involvement through climate) and interaction (climate enhancing the ability relationship and/or ability enhancing the climate relationship). The unique linear contributions remain the same.

The standardized regression equation yields a regression weight for each of the four simple terms (two individual variables and two climate variables) plus a weight for the product term. By algebraic manipulation the product term was combined with the student ability term and student ability factored out. The result is a weight for student ability which is a function of shared climate perceptions of Coordination.[2] As both

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[2]Ability was taken as a function of climate because the climate differences represent the natural grouping (i.e., classes) for this sample.

the weight for ability and Figure 1 indicate, student ability has a stronger relationship to student performance when class Coordination is high.

As argued in the introduction, the existence of a significant interaction does not necessarily imply differences in predictability. To examine this possibility, students were grouped according to the Coordination score of their class. Thus, low Coordination students were those in the lowest one-third of the classes (270 students, Coordination less than 3.005). High Coordination students were in the top one-third of the classes (293 students, Coordination greater than 3.27). Medium Coordination students were in the 24 classes between 3.005 and 3.27 on the Coordination scale. Means and standard deviations for these classes on the relevant variables appear in Table 5. Note that in addition to the expected differences in Coordination, climate scores across the three groups, Knowledge and Skill levels and performance levels also vary appropriately from the low to high group. The remaining variables tend to be stable across groups.

Table 6 presents the data relevant to the issue of predictive accuracy.

First, as anticipated from the significant main effects of Coordination on performance, and as noted above, mean performance increases from low to medium to high Coordination students. These mean differences apparently reflect not only the main effects of Coordination but also the facilitating effect Coordination may have on ability and the potential effect of increased Knowledge and Skill in the high Coordination classes. In other words, these means reflect the most complete general statement about the gross relationship between Coordination (confounded and otherwise)

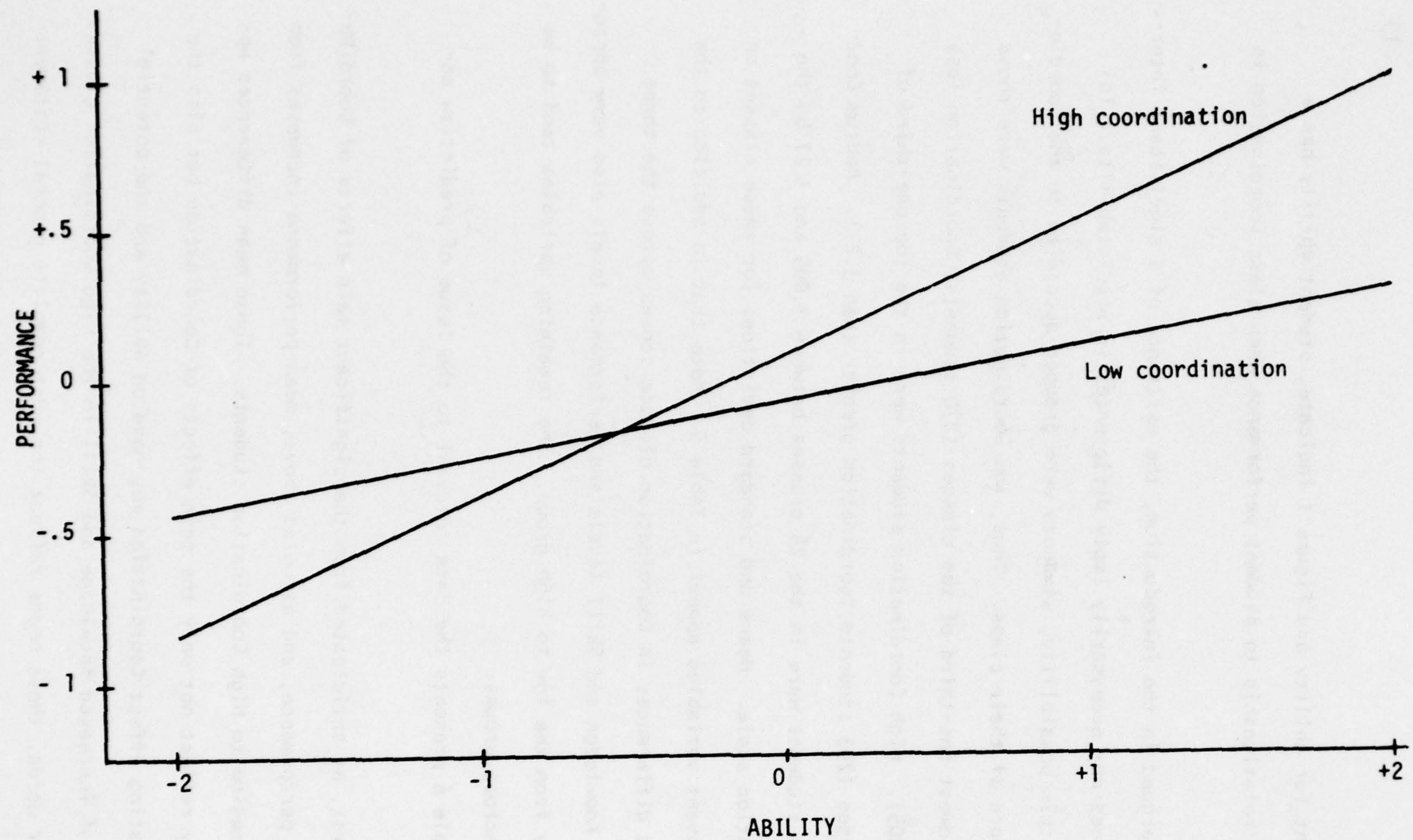

Figure 1. Student Ability/Class Coordination Interaction on Student Performance (Plotted in _z_-scores).

Table 5

Means and Standard Deviations of Variables

in Coordination Subgroup Analysis

	Coordination Subgroup					
	Low		Medium		High	
	(N = 270)		(N = 231)		(N = 293)	
	$\overline{X}$	σ	$\overline{X}$	σ	$\overline{X}$	σ
Ability	3.13	.86	3.18	.80	3.18	.75
Student Involvement	3.44	.61	3.44	.60	3.60	.64
Knowledge and Skill	3.80	.26	3.77	.32	4.07	.26
Coordination	2.94	.09	3.16	.05	3.37	.10
Performance	73.10	13.89	75.17	13.02	78.23	12.93

Table 6

Performance Variance, Error Varianc. and Correlations

for Three Levels of Coordination

Coordination Group	N	Performance Variance	Full Composite Prediction Error Variance[a]	$\underline{r}$[b]	Ability Prediction Error Variance[c]	$\underline{r}$
Low	270	193.05	162.27	.40	133.18	.31
Medium	231	169.82	132.46	.47	113.76	.33
High	293	167.39	124.26	.51	107.13	.36

[a] Low and high groups significantly different at $\underline{p} < .05$.

[b] Indicates correlation between predicted performance and actual performance where prediction is based on the regression equation derived from the full sample.

[c] Low and high groups significantly different at $\underline{p} < .05$.

and level of student performance.

Table 6 also shows performance variance and error variance for students within each of the three classifications. Error variance was calculated by first using the raw score regression equation derived for the total sample to calculate a predicted score (Y') for each student. The following formula was then used within each group to calculate error variance: $\frac{\Sigma(Y - Y')^2}{N}$.

Performance variance and error variance both show a decreasing pattern from low to medium to high Coordination classes. For the high and low Coordination groups the difference in error variance is significant $F = \frac{162.27}{124.26} = 1.31$, $p < .05$).

The difference in performance variance (though non-significant) suggests a higher correlation between predicted performance and actual performance in low Coordination classes, while the difference in error variance suggests a higher correlation for high Coordination classes. In fact, the correlation between predicted performance and actual performance increases from low to high Coordination classes, but the difference between them only approaches the traditional level of significance ($z = 1.64$, $p < .10$). Thus, within-group accuracy of prediction (i.e., within group r) is at best marginally better for high Coordination groups, while prediction accuracy compared to actual performance (error variance) is significantly better for high Coordination groups. This pattern occurs in spite of a contradictory trend for performance variance to decrease in high Coordination groups.

Similar conclusions are reached when ability is examined by itself. That is, the difference between the ability/performance correlations are not significant at the .05 level, however the error variances are different ($p < .05$).

DISCUSSION

Comparing analyses of individual perceptions and shared perceptions of climate, and comparing individual differences variables and climate variables within these analyses, a number of significant points can be discussed. However, perhaps the most significant aspect of the results is that, whichever analysis is examined, a relatively large proportion of the variance in student class performance is accounted for with relatively few indices taken from a complex setting.

Personnel selection writers have long been lamenting Ghiselli's (1956) finding that the average published ability/performance correlation is in the neighborhood of .35. Similarly, motivation theorists (e.g., Miner & Dachler, 1973; Howard, 1976) have commented that motivation variables do not typically exceed a correlation of .35. Cronbach and Snow (Note 1) comment on the failure of educational researchers to calculate etas for their experimental treatments, but one suspects that these, too, would not be expected to often fall above .35.

If the results for this study are examined as zero order effects only, the pattern of .35 results is repeated. That is, ability alone correlated .33 with performance. Student involvement, which can be interpreted as a behavioral description of course motivation, correlated .38 with performance. The climate indices failed to reach the .35 expectation with the highest individual perception correlation reaching .21 and the highest shared perception reaching only .14.

With the "failure" of any one class of variables to account for more than 15% of performance variance, the next theoretical step was to argue for examination of both individual and situational variables at the same time in interaction (Cronbach, 1957). That approach had led to some success (e.g. House & Mitchell, 1974; Kerr et al., 1974) and some disappointments (Cronbach, 1975). However, in the rush to find interactions, there seems to have been a tendency to overlook the importance of the simple additive effects of variables of different kinds (Schneider, 1978b). Thus, in the two analyses of this study, only one interaction out of sixteen possibilities was found to be statistically significant. While that one interaction allows a number of interesting supplementary analyses that are not meaningful in the absence of interaction effects, one should not overlook the fact that a considerably larger proportion of the performance variance is accounted for by the simple additive combination of variables ($R = .50$ for the individual analysis and .50 for the climate analysis without the interaction) than by any one kind of variable by itself (ability, motivation, climate). That is, 25% of the variance in performance is accounted for by six possible variables (two individual and four climate) which are intertwined such that only four of them are included in the regression function.

Comparison between individual differences and climate variables would seem to support the contention that individual differences are the strongest correlate of performance. On the other hand, (a) the teacher activities assessed as climate (either via individual perceptions or shared perceptions) did relate to student performance, and (b) there remains a large part of performance which is unexplained, some of which may be attributable to other unmeasured teacher activities.

Comparison between the individual perceptions of climate and the shared perceptions of climate reveal two differences. First, the climate variables that entered the regression functions varied depending upon their use as individual or climate data. That is, while Coordination entered the equation in each case, Critical Demands entered the individual analysis equation and Knowledge and Skill entered the climate analysis equation. Because all four climate variables, taken as either the individual perception or the shared perceptions, were significantly related to performance (both before and after ability was controlled), the result that Knowledge and Skill entered one analysis while Critical Demands entered the other may be more a function of the intercorrelation of the variables rather than their separate relationships to performance. Since (a) at any step in the regression procedure, the variable chosen for entry is the one with the largest part correlation, and (b) the differences between these part correlations is not tested, the selection of one variable over another may be partly a function of chance. Perhaps the most appropriate conclusion is simply that Knowledge and Skill and Critical Demands, and for that matter Consideration, share overlapping associations with student performance.

The second difference between the individual analysis and the climate analysis is the appearance of the Coordination X ability interaction in the climate analysis. A possible explanation lies in the low inter-rater reliability of the shared perception of Coordination coupled with the significant correlation between ability and individual perceptions of Coordination. Thus, one could argue that differences in individual ability lead to differences in the way students perceive class Coordination, and these differences in perception lead to low agreement between students within each class. If one could assume that there is some "true" level of class Coordination which, although students do not agree, is approximated by the average of their perceptions, then one could also argue that the ability X Coordination interaction indicates that greater coordination of readings, lectures and examinations, does facilitate the learning of higher ability students more than that of lower ability students. If the interaction term is conceptualized as an adjustment for the main effect of Coordination, the adjustment is not needed using the individual perceptions because the perceptions themselves carry the adjustment. That is, the interaction is confounded in the individual perceptions of Coordination. By aggregating individual perceptions into an average perception, that ability contamination is reduced (at the expense of reliability) allowing the interaction to appear.

Further examination of the Coordination X ability interaction, i.e., by examining Coordination subgroups, revealed that high Coordination does not function to overcome the deficiencies of low ability students, but rather allows high ability students to express their abilities as Schneider (1978a) hypothesized. Thus, students in higher Coordination class have a higher group mean and their performance is more predictable (as defined by the error variance) using ability by itself or using the complete ability/Student Involvement/climate prediction equation.

Reference Notes

1. Cronbach, L. J. & Snow, R. E. Final report: Individual differences in learning ability as a function of instructional variables. Stanford: Stanford University School of Education, 1969.

2. Frederiksen, N. Some effects of organizational climates on administrative performance. (ETS RM 66-21). Princeton, N.J.: Educational Testing Service, 1966.

References

Atkinson, J. W. Motivational determinants of intellective performance and cummulative achievement. In J. W. Atkinson and J. O. Raynor (Eds.) Motivation and Achievement. New York: Wiley, 1974

Cronbach, L. J. The two disciplines of scientific psychology. American Psysholohist, 1957, 12, 671-684.

Cronbach, L. J. Beyond the two disciplines of scientific psychology. American Psychologist, 1975, 30, 116-127.

Cohen, J., & Cohen, P. Applied multiple regression/correlation analysis for the behavioral sciences. New York: John Wiley, 1975.

Dunnette, M. D. A modified model for test validation and selection research. Journal of Applied Psychology, 1963, 47, 317-323

Fiedler, F. E. Validation and extension of the contingency model of leadership effectiveness: A review of empirical findings. Psychological Bulletin, 1971, 76, 128-148.

Ghiselli, E. E. The placement of workers: Concepts and problems. Personnel Psychology, 1956, 9, 1-16.

Greene, C. N. The reciprocal nature of influence between leader and subordinate. Journal of Applied Psychology, 1975, 60, 187-193.

Hackman, J. R., & Oldham, G. R. Development of the job diagnostic survey. Journal of Applied Psychology, 1975, 60, 159-170.

Hellriegel, D., & Slocum, J. W., Jr. Organizational climates: Measures, research and contingencies. Academy of Management Journal, 1974, 17, 255-280.

Hoffman, R. G. Student descriptions of instructional characteristics as relevant indices of teaching effectiveness. (Doctoral dissertation, University of Maryland, 1976). Dissertation Abstracts International, 1976, 37, 5869-B. (University Microfilms No. 77-10, 276).

House, R. J., & Mitchell, T. R. Path-goal theory of Leadership. Journal of Contemporary Business, 1974, Autumn, 81-97.

Howard, A. Intrinsic motivation and its determinants as factors enhancing the prediction of job performance from ability. (Doctoral dissertation, University of Maryland, 1976).

Jackson, P. W. The teacher and individual differences. In N. B. Henry (Ed.), Individualizing Instruction, Chicago: University of Chicago Press, 1962.

Kerlinger, F. N., & Pedhazur, E. J. Multiple regression in behavioral research. New York: Holt, Rinehart and Winston, 1973.

Kerr, S., Schriesheim, C. A., Murphy, C. J. & Stogdill, R. M. Toward a contingency theory of leadership based upon the consideration and initiating structure literature. Organizational Behavior and Human Performance, 1974, 12, 62-82.

Landy, F. J. & Trumbo, D. A. Psychology of work behavior. Homewood, Ill: The Dorsey Press, 1976.

Miner, J. B., & Dachler, H. P. Personnel attitudes and motivation. Annual Review of Psychology, 1973, 24. 379-402.

Mobley, W. H., & Locke, E. A. The relationship of value importance to satisfaction. Organizational Behavior and Human Performance, 1970, 5, 463-483.

Schneider, B. Person-situation selection: A review of some ability-situation interaction research. Personnel Psychology, 1978, 31, 281-297. (a)

Schneider, B. Implications of the conference: A personal view. Personnel Psychology, 1978, 31, 299-304. (b)

Schneider, B. Organizational climates: An essay. Personnel Psychology, 1975, 28, 447-449.

Schneider, B., & Snyder, R. A. Some relationships between job satisfaction and organizational climate. Journal of Applied Psychology, 1975, 60, 318-328.

Sharon, A. T., & Bartlett, C. J. Effects of instructional conditions in producing leniency on two types of rating scales. Personnel Psychology, 1969, 22, 251-263.

Footnotes

[1]Other assessments of the class climate could reduce the apparent impact of Student Involvement. That is, Student Involvement may mediate other unmeasured aspects of classroom climate.

[2]Ability was taken as a function of climate because the climate differences represent the natural grouping (i.e., classes) for this sample.

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