POTENTIAL PREDICTIVE VALIDITY LOSS IN ARBITRARILY WEIGHTED PSYCHOLOGICAL CONSTRUCT COMPOSITES

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The recommendation for analysis in correlational studies involving change or discrepancy score concepts is clear and consistent, "avoid the use of change scores and allow the individual variables to function separately in the analysis" (Cronbach and Furby, 1970; Linn and Slinde, 1977). This recommendation would appear to be appropriate for any arbitrarily weighted composite, whether the intent is to define a change or discrepancy construct or a summated (additive) construct. However, in spite of this recommendation, the appeal of the concept of arbitrarily weighted composite constructs persists. Educational and psychological theorists continue to think of equally weighted composites of two variables as attractive methods for defining constructs thought to have significance within the framework of a theoretical network of variables. Constructs have been defined merely by adding or subtracting the scores of two other variables, thus forming a composite through the arbitrary assignment of a "plus one" or a "minus one" weight to the original variables. These arbitrarily weighted composites commonly have been used as predictor or criterion variables in correlational studies. Examples include the following:

1) Job satisfaction has been defined both as a change construct (difference between real and ideal ratings of job facets) and as a summated composite of ratings of job facets (Wanous and Lawley, 1972.)

2) Self-concept has been defined as a difference construct (ideal vs. real) (Wylie, 1973).

3) Salkind and Wright (1977) have reconceptualized the measurement components of cognitive tempo to define a weighted composite impulsivity construct based on standardized error and latency scores ($I = z_1 - z_e$) and a weighted composite efficiency construct ($E = z_1 + z_e$).

4) An "attitude toward disability" was operationally defined as the difference in a "spread score" and an "isolation score" (Cordaro and Shonty, 1969).

5) The concept of Erg in Catell's theory of motivation where Erg = Drive - Goal Satisfaction (Madsen, 1961).

6) Use of change or gain commonly obtained in developmental studies, e.g., intellectual growth (McCall & Johnson, 1972).

7) The study of attitude change and its correlates (Triandis, 1971).

While study of change, growth or discrepancies is a fundamental focus of much scientific inquiry in education and psychology, the methodological inadequacies of using raw change scores as variables in data analyses have been clearly identified in terms of both statistical and measurement deficiencies (e.g., Cronbach and Furby, 1970; Harris, 1963; Linn and Slinde, 1977; McNemar, 1958; O'Connor, 1972; Wall and Payne, 1973). Cronbach and Furby (1970) included in their discussion of gain scores the use of difference scores as definitions of constructs. They indicated that, "there is little reason to believe and much empirical reason to disbelieve the contention that some arbitrarily weighted function of two variables will properly define a construct. More often, the profitable strategy is to use the two variables separately in the analysis so as to allow for complex relationships" (p. 79). Linn and Slinde (1977) agreed with the latter conclusion to allow each variable to assume a weight in a linear composite determined by the data rather than assign arbitrary weightings of "one" and a "minus one." Wall and Payne (1973) essentially reached the same conclusion stating "... we strongly agree with this advice offered by Cronbach and Furby (1970) that 'deficiency,' 'change' or 'gain' scores should be avoided, and raw scores only should be used" (p. 326).

In spite of the above recommendations, researchers in psychology and education continue to use "change," "gain" or "difference" score extensively. Reflecting this persistence, recent writings on change scores have attempted to identify those situations and/or methodologies where the use of change scores is meaningful, useful and methodologically sound (Corder-Bolz, 1978; Labouvie, 1980; Maxwell and Howard, 1981; Zimmerman and Williams, 1982a,b). Zimmerman and Williams, in particular, have indicated that "... under realistic experimental conditions, change and growth measures determined from individual examinee's test scores can have excellent predictive value" (p. 962). They identified conditions under which change scores can have high predictive potential and can be reliable. They also demonstrated that the potential ranges of the predictive validity and reliability of change scores are dependent on the ratio of the standard deviations of the two measures (X and Y) involved in the change score. As this latter ratio deviates from one (equality of variances), the potential ranges of change score (Y - X) validity and reliability coefficients increase dramatically. This is particularly true for the validity coefficient when Y and X are differentially correlated with the criterion variable Z, i.e., $r_{yz} \neq r_{xz}$.

The evidence presented by Williams and Zimmerman (1982a) would appear to be at odds with previous recommendations. However, Glasnapp and Raèissi (1983) demonstrate that the conditions identified by Williams and Zimmerman under which high change score predictive validity coefficients result also define suppression conditions within the context of the three variable linear regression model. They reexamine the concept of change score composites by relating them to suppression conditions and map the domain of conditions necessary for the emergence of a weighted change score composite as the underlying construct in a regression model. Glasnapp and Raeissi also address the information loss from the data when arbitrary assignment of weights is made.

Drawing on the work of Glasnapp and Raeissi (1983), the intent of the present paper is to demonstrate methodological inappropriateness of using arbitrarily weighted composites as defined variables in correlational research. The domain of potential information loss is mapped using a specific example from the literature. For the latter purpose, the cognitive tempo constructs of impulsivity (I-score) and efficiency (E-score) provide convenient arbitrarily weighted composites reflecting both a difference and a summated composite (Salkind and Wright, 1977).

Background Methodology

Glasnapp and Raeissi (1983) reexamine the concept of change score composites by relating them to suppression conditions within the context of the three variable linear regression model. They state,

> The rationale for recommending that Y and X be allowed to function separately in an analysis stems from the arbitrariness of assigning weights of 1.00 and -1.00 when change score composites of Y-X are formed. The arbitrary assignment of weights necessarily restricts the kind of information which will emerge about the relationship of Z to X and Y. Whether investigating the relationship of Y-X to Z or some least squares linear composite of Y and X to Z, the information used is embodied in the values of the intercorrelations r_{xz}, r_{yz}, and r_{xy} and the variability indices s_x, s_y and s_z. If a change score construct has a dominant relationship to Z in the data, it will emerge and be defined by the regression of Z on X and Y as separate variables. Weights defined by the data through least squares will maximize the relationship between Z and the linear composite of X and Y and will identify the dominant structure of the composite containing X and Y while also identifying the relative contributions of X and Y to the composite and its relationship to Z.
>
> For a change score composite to emerge as the dominant underlying dimension in the relationship of X and Y to Z, the regression weight for Y would be positive and the weight for X would necessarily be negative. Assuming the variables are all scaled in the same positive direction, a negative weight can occur for X only if X has the characteristics of a suppressor variable in the regression model. When a potential change score composite is examined from a perspective which views X as a suppressor variable, the conditions under which the concept of change will result as a dominant variable can be further delineated (pp. 6 and 7).

While Glasnapp and Raeissi focused entirely on change or discrepancy composites as defined by regression suppression conditions, the complementary conditions for redundancy in a regression model can be identified as the conditions for which a summated composite will occur from a regression analysis of the data.

Given a three variable regression model (two predictors and one criterion variable) the conditions necessary for suppression and redundancy among the predictors have been well defined (Conger, 1974; Tzelgou and Stern, 1978). Three suppressor classifications have been identified: classical (Horst, 1941), negative (Darlington, 1968) and reciprocal (Conger, 1974) suppression. Conger has shown that under all suppression conditions, the inclusion of the suppressor variable in the regression equation increases the predictive validity (beta weight) of the other variable in the equation. Assuming a three variable regression model with X as the suppressor variable, Y as the predictor, and Z as the criterion, the following define conditions where each type of suppression will result.

<u>Classical:</u> By definition, X will be a classical suppressor only when $r_{xz} = .00$ (Conger, 1974). Under this condition and the conditions that $r_{yz} > .00$ and $r_{xy} > .00$, X always will be a suppressor variable and enter the regression equation with a negative weight, thus defining a weighted change score composite.

<u>Negative:</u> Negative suppression occurs when a variable receives a negative weight upon inclusion in a regression equation when all variables have positive intercorrelations (defined by Darlington (1968) and labeled by Conger (1974)). Similarly, if the pairwise correlations are all negative, negative suppression has occurred if a variable enters the regression equation with a positive weight. Tzelgov and Stern (1978) have mapped the necessary domain of conditions for negative suppression in the three variable regression model. Given

that $r_{xy} > .00$, $r_{xz} > .00$ and $r_{yz} > r_{xz}$, negative suppression will occur if:

$$r_{xy} > \frac{r_{xz}}{r_{yz}} .$$

<u>Reciprocal:</u> The conditions for reciprocal suppression are slightly more complex than those for classical or negative suppression. In the latter two cases, the pairwise intercorrelations are consistent in sign ($r_{xz} = .00$ in the classical suppression case), but the sign of the regression coefficient for the suppressor variable is inconsistent; opposite that of r_{xz} and r_{yz}. In the reciprocal suppression case, the intercorrelations are inconsistent. One of the pairwise correlations must be of sign opposite the other two. In fact, the definition of reciprocal suppression is even more restrictive. Tzelgov and Stern (1978) have broadened Conger's (1974) formal definition and have shown that reciprocal suppression will occur whenever the intercorrelation between the two predictors (r_{xy}) is of opposite sign of the ratio of the two validity coefficients (r_{xz}/r_{yz}). Reciprocal suppression will occur for the following patterns of intercorrelation signs in the three variable case.

Pattern	r_{xy}	r_{xz}	r_{yz}
1	+	-	+
2	+	+	-
3	-	+	+
4	-	-	-

Redundancy: Occurs under all conditions where suppression does not occur.

I and E Score Composites

The pattern of intercorrelations for arbitrarily weighted composites of efficiency (E) and impulsivity (I) constructs (Salkind and Wright, 1977) were selected to be mapped and reexamined against the suppression and redundancy conditions within the three variable regression model. The definition of E and I scores represent examples of "summated" and "discrepancy" composite scores. As background, efficiency (E) and impulsivity (I) are two composite constructs defined by Salkind and Wright (1977) based on an arbitrary weighting and combining of error (e) and latency (l) scores obtained for an examinee from performance on Matching Familiar Figures Test (MFFT). The test is designed to measure the cognitive tempo of children. I and E scores are calculated by the following formula.

$$I_i = z_{e_i} - z_{l_i}$$
$$E = z_{e_i} + z_{l_i}$$

where I_i = impulsivity for the ith individual; E = efficiency for the ith individual; z_{e_i} = a standard score for the ith individual's total errors; and z_{l_i} = a standard score for the ith individual's mean latency. Large positive I scores indicate impulsivity, and large negative I scores indicate reflectivity. High positive E scores indicate inefficiency and high negative E scores indicate efficiency.

The opposite scaling of error scores from the typical direction for a variable (low scores are "good" scores) results in some confusion when conceptually relating error and latency scores to suppression and redundancy conditions. Errors generally will be negatively correlated with a criterion which is positively scaled. Latency scores will be positively correlated with the same criterion and errors and latency will be negatively correlated. In fact, reviews of studies investigating cognitive tempo have shown that correlations between errors and latency will range from -.04 to over -.70 with the median value in the -.50's. Given this pattern of intercorrelations, r_{ec} = negative, r_{lc} = positive, and r_{el} = negative, the impulsivity composite ($I = z_e - z_l$) really represents the summated composite while the efficiency score ($E = z_e + z_l$) is determined from a discrepancy composite. Reversing the error scale changes the signs of the weights for z_e in the I and E composites and also for r_{ec} and r_{el}. Under these conditions, the I-score composite corresponds to the redundant conditions and the E-score composite to the suppression conditions in the linear regression model.

Procedures

To map the domain of potential predictive validity loss for I- and E-scores within the three variable regression model, correlation coefficients between error scores (e) and a criterion (c) and latency scores (l) and the criterion were manipulated systematically. The correlation between errors and latency were fixed at two values (-.60 and -.30) to represent a range found in the literature. The values of r_{ec} used were -.80, -.60, -.40 and -.20. The values of r_{lc} ranged in .10 intervals between -1.00 and 1.00. The actual potential range for r_{lc} is dependent on the specific values of r_{ec} and r_{el} (Stanley and Wang, 1969). For manipulated combinations of r_{ec} and r_{el}, the following indices were calculated for each value of r_{lc}: 1) the least squares beta weight for errors and latency when regressing c on e and l; 2) $R^2_{c \cdot el}$, the multiple R^2 when regressing c on e and l; 3) r_{CI}^2, the squared correlation between c and the I composite; 4) r_{CE}^2, the squared correlation between c and the E composite; and 5) indices of information loss for I and E score composites formed by subtracting the ratio of $r_{CI}^2/R_{c\,el}^2$ and $r_{CE}^2/R_{c\,el}^2$ from one.

Results

The attached tables present the results for the various indices under the conditions manipulated. In each table, the values of r_{el} are identified which combine with the specific values of r_{el} and r_{ce} to define classical, negative or reciprocal suppression or redundant conditions within the least squares regression model. These conditions are labelled for specific values of r_{cl} in each table. It should be noted that the I and E composites are independent of each other (r_{IE} = .00). For this reason, they account for orthogonal portions of criterion score variance. In fact, I and E scores as separate predictors of the criterion partition the least squares regression multiple R squared into two orthogonal parts, i.e.,

$$R^2_{c \cdot el} = r_{CI}^2 + r_{CE}^2.$$

The information loss proportional indices, LOSS I and LOSS E, will always add to 1.00, as each gives the proportion of $R^2_{c \cdot el}$ which is unaccounted for by the relationship between the criterion and the arbitrarily weighted composite, I or E. The potential magnitudes of r_{CI}^2 and r_{CE}^2 thus are restricted by the size of the other coefficient and by the size of $R^2_{c \cdot el}$. It follows that the potential predictive validity coefficients for either I- or E-scores can only be high under those conditions where $R^2_{c \cdot el}$ is high. Also, if the validity coefficient is high for one arbitrarily weighted composite, it <u>cannot</u> be high for the other composite too.

REL=-0.60 RCE=-0.80

	RCL	BE	BL	R2C.EL	R2C.I	R2C.E	LOSS I	LOSS E
	1.00			Coefficient out of range				
Redundant	0.90	-0.41	0.66	0.92	0.90	0.01	0.01	0.99
	0.80	-0.50	0.50	0.80	0.80	0.00	0.00	1.00
	0.70	-0.59	0.34	0.72	0.70	0.01	0.02	0.98
	0.60	-0.69	0.19	0.66	0.61	0.05	0.08	0.92
	0.50	-0.78	0.03	0.64	0.53	0.11	0.18	0.82
Negative	0.40	-0.88	-0.13	0.65	0.45	0.20	0.31	0.69
	0.30	-0.97	-0.28	0.69	0.38	0.31	0.45	0.55
	0.20	-1.06	-0.44	0.76	0.31	0.45	0.59	0.41
	0.10	-1.16	-0.59	0.87	0.25	0.61	0.71	0.29
Classical	0.00	-1.25	-0.75	1.00	0.20	0.80	0.80	0.20
	-0.10							
	-0.20							
	-0.30							
	-0.40							
	-0.50							
	-0.60			Coefficients out of range				
	-0.70							
	-0.80							
	-0.80							
	-1.00							

Table 2

REL=-0.60 RCE=-0.60

	RCL	BE	BL	R2C.EL	R2C.I	R2C.E	LOSS I	LOSS E
Redundant	1.00	0.00	1.00	1.00	0.80	0.20	0.20	0.80
	0.90	-0.08	0.84	0.82	0.70	0.11	0.14	0.86
	0.80	-0.18	0.68	0.66	0.81	0.05	0.08	0.92
	0.70	-0.28	0.53	0.54	0.53	0.01	0.02	0.88
	0.80	-0.38	0.37	0.45	0.45	0.00	0.00	1.00
	0.50	-0.47	0.22	0.39	0.38	0.01	0.03	0.97
	0.40	-0.58	0.06	0.38	0.31	0.05	0.14	0.86
Negative	0.30	-0.66	-0.09	0.37	0.25	0.11	0.31	0.69
	0.20	-0.75	-0.25	0.40	0.20	0.20	0.50	0.50
	0.10	-0.84	-0.41	0.47	0.15	0.31	0.67	0.33
Classical	0.00	-0.84	-0.56	0.58	0.11	0.45	0.80	0.20
Reciprocal	-0.10	-1.03	-0.72	0.69	0.08	0.61	0.89	0.11
	-0.20	-1.13	-0.88	0.85	0.05	0.80	0.94	0.06
	-0.30							
	-0.40							
	-0.50							
	-0.60							
	-0.70			Coefficients out of range				
	-0.80							
	-0.90							
	-1.00							

Table 3

REL=-0.60 RCE=-0.40

	RCL	BE	BL	R2C.EL	R2C.I	R2C.E	LOSS I
	1.00	Coefficient out of range					
	0.90	0.22	1.03	0.84	0.53	0.31	0.37
Negative	0.80	0.12	0.87	0.65	0.45	0.20	0.31
	0.70	0.03	0.72	0.49	0.38	0.11	0.23
	0.60	-0.06	0.56	0.36	0.31	0.05	0.14
	0.50	-0.16	0.41	0.27	0.25	0.01	0.05
Redundant	0.40	-0.25	0.25	0.20	0.20	0.00	0.00
	0.30	-0.34	0.09	0.17	0.15	0.01	0.08
	0.20	-0.44	-0.06	0.16	0.11	0.05	0.31
Negative	0.10	-0.53	-0.22	0.19	0.08	0.11	0.59
Classical	0.00	-0.63	-0.38	0.25	0.05	0.20	0.80
	-0.10	-0.72	-0.53	0.34	0.03	0.31	0.92
	-0.20	-0.81	-0.69	0.46	0.01	0.45	0.87
Reciprocal	-0.30	-0.91	-0.84	0.62	0.00	0.61	0.99
	-0.40	-1.00	-1.00	0.80	0.00	0.80	1.00
	-0.50						
	-0.60						
	-0.70						
	-0.80	Coefficients out of range					
	-0.90						
	-1.00						

Table 4

REL=-0.60 RCE=-0.20

	RCL	BE	BL	R2C.EL	R2C.I	R2C.E	LOSS I
	1.00	Coefficient out of range					
	0.90	0.53	1.22	0.88	0.38	0.61	0.62
	0.80	0.44	1.06	0.78	0.31	0.45	0.58
	0.70	0.34	0.91	0.57	0.25	0.31	0.55
Negative	0.60	0.25	0.75	0.40	0.20	0.20	0.50
	0.50	0.18	0.59	0.27	0.15	0.11	0.42
	0.40	0.08	0.44	0.18	0.11	0.05	0.31
	0.30	-0.03	0.28	0.09	0.08	0.01	0.14
Redundant	0.20	-0.13	0.12	0.05	0.05	0.00	0.00
Negative	0.10	-0.22	-0.03	0.04	0.03	0.01	0.31
Classical	0.00	-0.31	-0.19	0.06	0.01	0.05	0.80
	-0.10	-0.41	-0.34	0.12	0.00	0.11	0.97
	-0,20	-0.50	-0.50	0.20	0.00	0.20	1.00
	-0.30	-0.59	-0.66	0.32	0.00	0.31	0.99
Reciprocal	-0.40	-0.69	-0.81	0.46	0.01	0.45	0.97
	-0.50	-0.79	-0.97	0.64	0.03	0.61	0.96
	-0.60	-0.88	-1.13	0.85	0.05	0.80	0.94
	-0.70						
	-0.80	Coefficients out of range					
	-0.90						
	-1.00						

Table 5

REL=-0.30 RCE=-0.80

	RCL	BE	BL	R2C.EL	R2C.I	R2C.E	LOSS I	LOSS
	1.00							
	0.90			Coefficients out of range				
Redundant	0.80	-0.62	0.62	0.98	0.98	0.00	0.00	1.00
	0.70	-0.65	0.51	0.87	0.87	0.01	0.01	0.99
	0.60	-0.68	0.40	0.78	0.75	0.03	0.04	0.96
	0.50	-0.71	0.29	0.71	0.65	0.06	0.09	0.91
	0.40	-0.75	0.18	0.67	0.55	0.11	0.17	0.83
	0.30	-0.78	0.07	0.64	0.47	0.18	0.28	0.72
Negative	0.20	-0.81	-0.04	0.64	0.38	0.26	0.40	0.60
	0.10	-0.85	-0.15	0.66	0.31	0.35	0.53	0.47
Classical	0.00	-0.88	-0.26	0.70	0.25	0.46	0.65	0.35
Reciprocal	-0.10	-0.91	-0.37	0.77	0.19	0.58	0.75	0.25
	-0.20	-0.95	-0.48	0.85	0.14	0.71	0.84	0.16
	-0.30	-0.98	-0.59	0.96	0.10	0.86	0.90	0.10
	-0.40							
	-0.50							
	-0.60							
	-0.70			Coefficients out of range				
	-0.80							
	-0.90							
	-1.00							

Table 6

REL=-0.30 RCE=-0.60

	RCL	BE	BL	R2C.EL	R2C.I	R2C.E	LOSS I	LOSS
	1.00			Coefficient out of range				
	0.90	-0.36	0.79	0.93	0.87	0.08	0.07	0.93
Redundant	0.80	-0.40	0.68	0.78	0.75	0.03	0.04	0.96
	0.70	-0.43	0.57	0.66	0.65	0.01	0.01	0.99
	0.60	-0.46	0.46	0.55	0.55	0.00	0.00	1.00
	0.50	-0.49	0.35	0.47	0.47	0.01	0.02	0.98
	0.40	-0.53	0.24	0.41	0.38	0.03	0.07	0.93
	0.30	-0.56	0.13	0.38	0.31	0.06	0.17	0.83
	0.20	-0.59	0.02	0.36	0.25	0.11	0.32	0.68
Negative	0.10	-0.63	-0.09	0.37	0.19	0.19	0.49	0.51
Classical	0.00	-0.66	-0.20	0.40	0.14	0.26	0.65	0.35
Reciprocal	-0.10	-0.69	-0.31	0.45	0.10	0.35	0.78	0.22
	-0.20	-0.73	-0.42	0.52	0.06	0.46	0.88	0.12
	-0.30	-0.76	-0.53	0.61	0.03	0.58	0.94	0.06
	-0.40	-0.79	-0.64	0.73	0.02	0.71	0.98	0.02
	-0.50	-0.82	-0.75	0.87	0.00	0.86	1.00	0.00
	-0.60							
	-0.70			Coefficients out of range				
	-0.80							
	-0.90							
	-1.00							

Table 7

REL=-0.30 RCE=-0.40

	RCL	BE	BL	R2C.EL	R2C.I	R2C.E	LOSS I	L(
	1.00	Coefficient out of range						
Redundant	0.90	-0.14	0.86	0.83	0.65	0.18	0.22	0.
	0.80	-0.18	0.75	0.67	0.55	0.11	0.17	0.
	0.70	-0.21	0.64	0.53	0.47	0.06	0.12	0.
	0.60	-0.24	0.53	0.41	0.38	0.03	0.07	0.
	0.50	-0.27	0.42	0.32	0.31	0.01	0.02	0.
	0.40	-0.31	0.31	0.25	0.25	0.00	0.00	1.
	0.30	-0.34	0.20	0.20	0.19	0.01	0.04	0.
	0.20	-0.37	0.09	0.17	0.14	0.03	0.17	0.
Negative	0.10	-0.41	-0.02	0.16	0.10	0.06	0.40	0.
Classical	0.00	-0.44	-0.13	0.18	0.06	0.11	0.65	0.
Reciprocal	-0.10	-0.47	-0.24	0.21	0.03	0.18	0.84	0.
	-0.20	-0.51	-0.35	0.27	0.02	0.26	0.84	0.
	-0.30	-0.54	-0.46	0.35	0.00	0.35	0.99	0.
	-0.40	-0.57	-0.57	0.46	0.00	0.46	1.00	0.
	-0.50	-0.60	-0.68	0.58	0.00	0.58	0.99	0.
	-0.60	-0.64	-0.79	0.73	0.02	0.71	0.98	0.
	-0.70	-0.67	-0.90	0.90	0.03	0.86	0.96	0.
	-0.80	Coefficients out of range						
	-0.90							
	-1.00							

Table 8

REL=-0.30 RCE=-0.20

	RCL	BE	BL	R2C.EL	R2C.I	R2C.E	LOSS I	LOS
	1.00	Coefficient out of range						
Negative	0.90	0.08	0.82	0.82	0.47	0.35	0.43	0.5
	0.80	0.04	0.81	0.64	0.38	0.28	0.40	0.6
	0.70	0.01	0.70	0.48	0.31	0.18	0.38	0.6
Redundant	0.60	-0.02	0.59	0.36	0.25	0.11	0.32	0.6
	0.50	-0.05	0.48	0.25	0.18	0.06	0.25	0.7
	0.40	-0.08	0.37	0.17	0.14	0.03	0.17	0.8
	0.30	-0.12	0.28	0.10	0.10	0.01	0.07	0.9
	0.20	-0.15	0.15	0.08	0.06	0.00	0.00	1.0
	0.10	-0.18	0.04	0.04	0.03	0.01	0.17	0.8
Classical	0.00	-0.22	-0.07	0.04	0.02	0.03	0.65	0.3
Reciprocal	-0.10	-0.25	-0.18	0.07	0.00	0.06	0.84	0.0
	-0.20	-0.29	-0.29	0.11	0.00	0.11	1.00	0.0
	-0.30	-0.32	-0.40	0.18	0.00	0.18	0.98	0.0
	-0.40	-0.35	-0.51	0.27	0.02	0.26	0.94	0.0
	-0.50	-0.38	-0.62	0.38	0.03	0.35	0.91	0.0
	-0.60	-0.42	-0.73	0.52	0.06	0.46	0.88	0.1
	-0.70	-0.45	-0.84	0.67	0.10	0.58	0.86	0.1
	-0.80	-0.48	-0.95	0.85	0.14	0.71	0.84	0.1
	-0.90	Coefficients out of range						
	-1.00							

When examining the pattern of results for the domain of conditions investigated, several salient points are evident. First, the efficiency (E) composite validity coefficient is higher than the impulsivity (I) coefficient only under moderate to extreme suppression conditions. For less potent suppression conditions and all redundant regression conditions, the I-score validity coefficient will be closer to $R_{c \cdot el}$ and result in less information loss as a predictive index. These patterns are consistent with the underlying characteristics of the arbitrarily weighted I and E composites. The I composite is a summated composite and when redundant conditions exist, the underlying least squares regression model is a summated model. In contrast, the E composite is a discrepancy composite and when suppression conditions exist, the underlying least squares regression model is a discrepancy model. It is only for those conditions where the arbitrarily weighted I and E composites fit closely the underlying least squares regression model that the potential validity coefficients for I or E are maximized. For all other conditions, some information loss will be evidenced. It should be noted, however, that there is always a trade-off between the validity coefficients for I and E. When the conditions are such that one is maximized, the other must of necessity be minimized.

The latter point is best illustrated by identifying those conditions where an equally weighted linear composite will result from the regression analysis, i.e., where the absolute value of the beta weight for errors (β_e) is equal to the absolute value of the beta weight for latency (β_1). The sign of the weights will determine whether an underlying, equally weighted least squares composite is a discrepancy or a summated composite. The data from the tables verify the conditions identified by Glasnapp and Raeissi (1983) which will result in an equally weighted least squares composite. The absolute values of the beta weights for errors and latency will be equal when the absolute values of the validity coefficients for errors and latency are equal, i.e., $|\beta_e| = |\beta_l|$ when $|r_{ce}| = |r_{cl}|$. Given the sign pattern of intercorrelations expected among errors, latency and the criterion, an equally weighted summated composite will result when r_{ce} equals r_{cl}, but the coefficients are of opposite sign. For example, when $r_{ce} = -.40$ and $r_{cl} = .40$, $\beta_e = -.25$ and $\beta_l = .25$ for $r_{el} = -.60$ and $\beta_e = -.31$ and $\beta_l = .31$ for $r_{el} = -.30$. In both instances, redundant regression conditions are defined and r_{CI} is maximized, while $r_{CE} = .00$, i.e., $r_{CI}^2 = R_{c.el}^2$. In contrast, when reciprocal suppression conditions are defined, e.g., $r_{ce} = -.40$ and $r_{cl} = -.40$, the beta weights are equal, but a discrepancy composite is defined and the validity coefficients for E-scores are maximized. Under the conditions that $r_{ce} = -.40$, $r_{cl} = -.40$, and $r_{el} = -.30$, $\beta_e = -.57$, $\beta_l = -.57$ and $r_{CE}^2 = R_{c.el}^2$ while $r_{CI} = .00$. When $r_{el} = -.60$, $\beta_e = -1.00$ and $\beta_l = -1.00$ and $r_{CE}^2 = R_{c.el}^2$. For all other conditions, where $|r_{ce}| \neq |r_{cl}|$, potential predictive information loss will occur when using the arbitrarily weighted I and E-score composites.

In addition to the potential predictive validity loss identified by the comparisons of r_{CI}^2 and r_{CE}^2 to $R_{c.el}^2$, the arbitrary equal weighting of error and latency scores in the I and E composites also masks the true relative contributions of each variable to the prediction of the criterion for the conditions specified. Comparisons of the beta weights for the least squares regression model indicate that the variable with the higher validity coefficient will dominate the weighted linear composite. When the validity coefficients are quite discrepant, the domination of the higher coefficient is quite severe. This is best illustrated if one examines the conditions for the values of r_{ce} which separate redundant from negative suppression conditions in the tables. Negative suppression will occur when $|r_{el}| > |r_{cl}/r_{ce}|$. However, when $|r_{el}| = |r_{cl}/r_{ce}|$ the beta weight for latency will equal zero, i.e., $\beta_1 = .00$, and errors will dominate totally the predictive relationship with the criterion. Approximate equality of r_{el} to the ratio of r_{cl}/r_{ce} is given in Table 1 for $r_{cl} = .80$. Under this condition, $\beta_e = -.78$ and $\beta_e = .03$. The I composite correlation with the criterion is still quite high ($r_{CI}{}^2 = .53$) leading to the conclusion that errors and latency conbine equally to predict the criterion at a high moderate level. Contrary to this conclusion, the truth is that the correlation of errors with the criterion ($r_{ce} = -.80$) results in the high value of $r_{ce}{}^2$ and latency score contribute little to the prediction.

Concluding Comments

While the constructs of impulsivity and efficiency have been used to illustrate the loss of information when using arbitrarily weighted composites in correlational studies, the procedures and results can be used to identify potential loss resulting from the use of any arbitrarily weighted composite. Only under those conditions where the least squares linear composite approximate an equally weighted composite will the arbitrarily weighted composites validity coefficient be maximized. Under other conditions where the arbitrarily weighted composite's validity coefficients appear high, the beta weights in the regression model indicate which variable dominates and contributes differentially to the apparently high validity coefficient.

Where I- and E- scores are used in correlational studies, the conditions where E will be highly correlated with a criterion are very restricted. As the discrepancy construct, high predictive validity coefficients will potentially occur only under moderate or extreme suppression conditions. Suppression conditions are ones which have been shown to occur infrequently in practice. This leads one to conclude that while an efficiency construct makes conceptual sense, the likelihood that it will occur as a salient construct from empirical data is extremely small. In contrast, the impulsivity construct will have higher validity coefficients over a wider range of conditions because it corresponds to the redundant conditions in a regression analysis. However, except when r_{ce} and r_{cl} are equal in magnitude, the potential predictive information level is reduced from $R^2_{c\cdot el}$. In addition to predictive information loss, the relative predictive importance of the individual variables forming the composite is lost when arbitrary weighting occurs.

The general conclusion arrived at by Glasnapp and Raeissi (1983) would seem to hold for I- and E- scores. If investigators insist on clinging to the summated or discrepancy concepts of I and E in studying relationships of cognitive tempo to other variables, they should examine their variables closely to see if the potential pattern of relationships follow those conditions which potentially could result in high I or E validity coefficients. Even then, information loss will occur if the variables are arbitrarily weighted. The recommended procedure evolving from the current examination is still to allow the individual error and latency variables to function separately in the analysis. If an E score composite is a dominant variable in the data, suppression conditions will occur among the intercorrelations, the regression model will identify the effective weights in the change score composite and the relationship with the criterion will be maximized. If an I-score composite is a dominant variable in the data, redundant conditions will occur among the intercorrelations, the regression model will identify the effective weights for errors and latency in the summated score composite and the relationship with the criterion will be maximized.

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