Suppressor variables are well known in the context of multiple regression analysis. Using several examples, the authors demonstrate that the different forms of the suppressor phenomenon described in the literature occur not only in prediction equations but also in the explanatory use of multiple regression, including structural equations models. Moreover, they show that the probability of their occurrence is relatively high in models with latent variables, in which the suppressed variable is corrected for measurement errors. Special attention will be paid to the two-wave model since this is particularly liable to the suppressor phenomenon. The occurrence of suppression in structural equations models is usually not foreseen and confronts researchers with problems of interpretation. The authors discuss definitions of the suppressor phenomenon, show how the unwary researcher can be warned against it, and present guidelines for the interpretation of the results.

Suppressor Variables in Path Models

Definitions and Interpretations

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Applications of multiple regression analysis in social scientific research can be roughly divided in two categories: explanatory and predictive (Pedhazur 1982). In sociology, the explanatory category prevails since in most studies involving multiple regression, the researcher tries to explain a dependent variable Y from one or more independent variables X_i. The independent variables are usually referred to as explanatory variables. In such situations, a researcher may also have a conception of the temporal order or the causal direction in which the independent variables are related to each other, in which case he or she may formulate hypotheses specifying which independent variables are influenced by others. In fact, the analysis then comprises a series of multiple regressions, and such a complex is called *path analysis* (Pedhazur 1982, chap. 15). Conversely, the explanatory use of simple multiple regression analysis can be regarded as a special case of path analysis. In this article, the general term *path*

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analysis will henceforth be used, which then also refers to simple multiple regression.

In psychology, in addition to this category, one can encounter a second, which comprises situations where unknown scores Y have to be predicted from known scores X_i (e.g., the prediction of school success or personnel selection). In such situations, the dependent variable Y is often referred to as the *criterion*, whereas the independent variables are called *predictors*. Within this context, the zero-order correlation of a predictor with the criterion is often referred to as *predictive validity.*

In all cases, the researcher attempts to realize a maximum proportion of explained variance in the dependent variable to achieve an optimum explanation or an optimum prediction, respectively. It is a well-known fact that this can be promoted by independent variables that correlate strongly with the dependent variable and weakly with each other.

Horst (1941) was the first to note that variables that do not have a high zero-order correlation with the dependent variable can contribute to an increased proportion of explained variance. In his classical example, he describes the way that the selection of World War II pilots could be improved by including not only a variable measuring their technical abilities in the prediction equation but also a variable assessing their verbal ability, even though the latter variable is itself unrelated to the criterion (navigating skills). He found that the verbal ability regressor had a negative coefficient when entered into the prediction equation. Horst introduced the term *suppressor variable* for such a variable.

McNemar (1945, 1969) explained the phenomenon in terms of *common elements*. According to McNemar, a useful predictor has, of course, many elements in common with the criterion but usually also irrelevant elements. A *suppressant* (which is the term McNemar used) is a variable that has no elements in common with the criterion but does have irrelevant elements in common with the predictor. If the predictor and suppressant are positively correlated, then the suppressant has a negative regression weight after inclusion in the regression equation. This reflects the fact that the irrelevant elements from the predictor are partialed out, which “purifies” the predictor and improves the prediction. In brief, the classical form of a suppressor variable is a variable that does not correlate with the dependent variable but does correlate with one or more independent variables.

It is no accident that the suppressor phenomenon was discovered in a study in which an optimization was sought for the prediction of a dependent variable, a typical psychological situation, or that it was the psychological literature in particular where this phenomenon caught attention. Suppressor variables are rarely associated with the application of multiple regression in explanatory studies, including path analysis. This is not surprising since the practical relevance of suppressor variables lies in their ability to increase the predictive power of another variable, whereas the main aim of path analysis is to test explanatory models of the relations between variables or theoretical concepts. Because, for path analysis, one usually has to confine oneself to selecting variables considered possibly of explanatory value, one is unlikely to include a variable of no apparent significance but only seeming to increase the explanatory significance of another variable.

Thus, the appearance of suppressor variables in a path model seems to be inherently contradictory. In this article, however, we will demonstrate with some examples that suppressor variables in path analysis, usually unintentionally, can indeed play an important role. It is important to acknowledge a suppressor structure in path analyses as well. After recognizing the phenomenon, one cannot discard suppressors when interpreting the results. We will also pay attention to these aspects.

TYPES AND DEFINITIONS OF SUPPRESSOR VARIABLES

Before we can illustrate the occurrence of suppressor variables in path analyses, it is necessary to describe the characteristics of a suppressor variable more clearly. There is more to it than is immediately obvious from the brief characterization above. On the contrary, the definition and characteristics of suppressor variables have been the subject of debate for several decades (Meehl 1945; Darlington 1968; Conger and Jackson 1972; Conger 1974; Cohen and Cohen 1975; Tzelgov and Stern 1978; Velicer 1978; Tzelgov and Henik 1981, 1985, 1991; Holling 1983; Smith, Ager, and Williams 1992).

TABLE 1: Examples of Suppressor Situations

Suppressor Situation	*1* r_{y1} (r^2_{y1})	*2* r_{y2} (r^2_{y2})	*3* r_{12}	*4* $b_{y1.2}$	*5* $b_{y2.1}$	*6* $r^2_{y(1.2)}$	*7* $r^2_{y(2.1)}$	*8* $R^2_{y.12}$
Classical	.40	.00	.707	.800	–.566			
	(.16)	(.00)				.320	.160	.320
Negative	.50	.10	.710	.865	–.514			
	(.25)	(.01)				.371	.131	.381
Reciprocal	.50	.30	–.270	.627	.469			
	(.25)	(.09)				.364	.204	.454

NOTE: See Velicer (1978, Table 1).

As it became clear that Horst's (1941) example was no more than a borderline case, seldom encountered in daily practice in its pure form, it was apparent that McNemar's (1969) explanation refers to more situations. A detailed, formal definition was therefore required, capable of representing the various situations in which suppression of irrelevant information occurs. As an introduction to these definitions, we present a few examples to show the typical outcomes for the estimates of the regression parameters resulting from the suppression phenomenon. The examples are displayed in Table 1 and are based on Velicer (1978, Table 1). Velicer limited himself to three-variable situations (with a dependent variable Y and two independent variables, which will be referred to as X_1 and X_2).

Columns 1, 2, and 3 of Table 1 include the bivariate correlations of three fictitious examples. Standardized partial regression coefficients are shown in columns 4 and 5; columns 6 and 7 refer to semipartial correlations (i.e., the correlations between Y and an independent variable from which the influence of another independent variable is partialed out). The additivity of the orthogonal variance components is a known relationship in multiple regression theory:

$$R^2_{y.12} = r^2_{y1} + r^2_{y(2.1)} = r^2_{y2} + r^2_{y(1.2)}. \tag{1}$$

This relationship can be recognized in Table 1: column 8 = column 1 (value between parentheses) + column 7 = column 2 (value between parentheses) + column 6.

From Table 1, the following observations can also be made:

1. The first example illustrates the *classical* suppressor condition mentioned above.
2. In the second example, two independent variables have a positive zero-order correlation with the dependent variable and correlate positively with each other. One of them receives a negative regression weight. This situation is referred to as *negative suppression*. Although the suppressor has relevant information in common with Y, they share fewer common elements than the common elements of irrelevant information shared by the suppressor and the other predictor.
3. The third situation concerns two variables that can act as good predictors. They also share, however, information that is irrelevant to Y, but with an opposite orientation. When both variables are included in the regression equation, they suppress a part of each other's irrelevant information. This case is called *reciprocal suppression*.
4. In all situations displayed in Table 1, it can be seen that after the inclusion of a second predictor, the absolute value of the regression coefficient increases.
5. In all situations displayed in Table 1, the squared semipartial correlation between Y and a variable X_i from which the other variable is partialed out exceeds the proportion of the variance of Y explained by X_i.

In the examples listed above, the suppressor phenomenon is clearly expressed in the results. However, the phenomenon can be masked by other effects, such as sample fluctuations, measurement errors, and the direction in which variables have been scaled. These influences may complicate identification of the suppressor phenomenon. For reasons of simplicity, we have not distinguished between population and sample or referred to measurement errors or the scaling of the variables. With reference to the latter, it should be noted that every numerical example is characterized by a pattern of correlations and is also representative of situations where that pattern appears after rescaling the variables.

Researchers searching for a definition of the suppressor phenomenon were aware of these effects and tried to protect their definitions from them. Darlington (1968) provided the following definition: If every independent variable, having within the population a correlation with the dependent variable unequal to zero, is scored such that this correlation becomes positive, then a suppressor variable is defined as a variable that—after inclusion in the regression equation—acquires a negative weight for the population. Thus, with this definition, *negative* *suppression* was added to the classical form of the suppressor phenomenon.

Conger (1974) used the characteristic mentioned under (4) as a starting point for his definition of a suppressor variable:

> A suppressor variable is defined to be a variable that increases the predictive validity of another variable (or set of variables) by its inclusion in a regression equation. This variable is a suppressor only for those variables whose regression weights are increased. (P. 36)

In a formula, variable X_2 is a suppressor for predictor X_1 (in relation to criterion Y) if

$$\beta_1 \cdot r_{y1} > r_{y1}^2 . \tag{2a}$$

Conger (1974) then scrutinized the situations that satisfy his definition, leading him to discover a third category of suppressor variables: *reciprocal suppressors*.

Velicer (1978:956) argued that a zero-order correlation and a regression coefficient are not wholly comparable and took characteristic (5) as the point of departure for his definition: A suppressor variable is an independent variable for which the squared zero-order correlation with the dependent variable is lower than the squared semipartial correlation between this independent variable and the dependent variable from which the other independent variables are partialed out.

Velicer (1978) observed that this definition can be applied to each of the three types of suppressor variables discussed by Conger (1974). The advantages of the definition are that it is based on a comparison of proportions of explained variance, and it is consistent with stepwise regression procedures. (Smith et al. [1992] emphasize additional advantages of Velicer's definition.) A disadvantage mentioned by Velicer himself is that "the definition will identify when a suppressor variable is present, but not specifically which variable is the suppressor. Designation of a variable as the suppressor would require knowledge of how a suppressor variable works" (p. 958). Tzelgov and Stern (1978) have shown that Conger's definition is more comprehensive than the definition of Velicer. They showed that there are situations when a variable that is designated a negative suppressor with respect

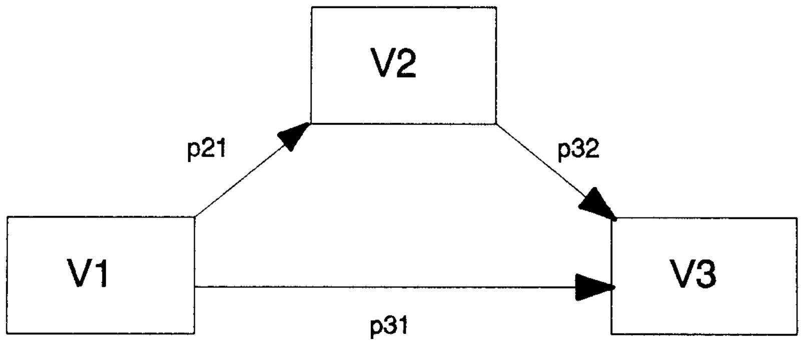

Figure 1: General Path Model for Three Variables

to another variable, according to Conger, does not meet Velicer's definition. We will elaborate on this point later.

The suppressor phenomenon not only shows up in three-variable situations. The definitions of Velicer (1978) and Conger (1974) are also applicable to situations with more than two independent variables. Suppose that, in such a situation, variable *S* meets Velicer's definition of a suppressor variable. With the help of formula (1), one can show that a linear composite of the other independent variables meets this definition as well. Thus, the linear composite can also be seen as the suppressor of variable *S*. In other words, it is possible for multiple independent variables in combination with each other to produce a suppressor effect.

Conger's (1974) definition can also be expanded to situations with more than two independent variables (Tzelgov and Henik 1991). Suppose a researcher has divided his or her independent variables into two disjunct sets. Variable *P* is the linear composite of independent variables from one set that explains *Y* optimally (according to the multiple regression technique). The correlation between *P* and *Y* is then equal to the multiple correlation coefficient R_{yp}. *S* is the linear composite of independent variables from the other set that optimally explains *Y* (with R_{ys} as the multiple correlation coefficient). Suppose further that β_p and β_s are the regression coefficients of the variables *P* and *S*, respectively, in the multiple regression of *Y* on *P* and *S*. In this case, a suppression situation occurs, and *S* is the suppressor variable with regard to *P* if

$$\beta_p > R_{yp}. \tag{2b}$$

SUPPRESSOR VARIABLES IN PATH MODELS

Before discussing the examples, we shall first outline the implications of the definition of suppression for the parameters in a path model. This will help later recognition of the phenomenon. Conger's (1974) definition allows an easy comparison between regression and path coefficients, and because of this advantage, we will use his definition as a point of departure. For the moment, we assume a saturated three-variable model as depicted in Figure 1. Because the difference between dependent and independent variables in path analyses is rather vague, the variables will be denoted as V_1, V_2, and V_3, and regression coefficients will be indicated with *p*s. Furthermore, we assume that both explanatory variables V_1 and V_2 are scaled such that r_{13} and $r_{23} > 0$. Path analysis now produces the following equations (see Pedhazur 1982:594):

$$r_{12} = p_{21}$$

and

$$r_{13} = p_{31} + p_{32} \bullet p_{21},$$

$$r_{23} = p_{32} + p_{31} \bullet p_{21}. \tag{3}$$

First, we examine the case in which the endogenous explanatory variable V_2 plays the role of suppressed variable. According to Conger (1974), in this case, $p_{32} > r_{23} > 0$. It follows that $r_{23} - r_{13} \bullet r_{12} > r_{23}(1 - r_{12}^2)$, or $r_{23} - r_{13} \bullet r_{12} > r_{23} - r_{23} \bullet r_{12}^2$, or

$$r_{13} \bullet r_{12} < r_{23} \bullet r_{12}^2. \tag{4}$$

Using equations (3) and (4), we shall analyze the different possible combinations of values for p_{31} and p_{21}. The second equation of system (3) makes it clear that neither p_{31} nor p_{21} can be equal to 0, since then $r_{23} = p_{32}$, and thus there would be no suppression. In addition, p_{31} and p_{21} cannot be of the same sign, because then it would follow that $p_{32} < r_{23}$.

This leaves only two possibilities:

(a) $p_{32} > 0$, $p_{31} < 0$, and $p_{21} > 0$. In this case, there is *negative* suppression. The correlation between V_2 and V_3 is partly based on a negative effect as a consequence of a spurious relationship. From equation (4), we can deduce a relationship between the correlation coefficients. From $r_{12} > 0$, it follows that

$$r_{12} > \frac{r_{13}}{r_{23}}. \tag{4a}$$

In this situation, V_1 is also a suppressed variable if $p_{31} < -r_{13}$. In this case, V_1 and V_2 are the suppressor and suppressed variable for each other. In the specific case $r_{13} = 0$, there is *classical* suppression.

(b) $p_{32} > 0$, $p_{31} > 0$, and $p_{21} < 0$. This is a case of *reciprocal* suppression. The correlation between V_2 and V_3 is again partly based on a negative effect as a consequence of a spurious relationship. Note that $r_{12} < 0$ automatically fulfills equation (4). In terms of correlation coefficients, this situation can be characterized as

$$r_{13} > 0,\ r_{23} > 0, \text{ and } r_{12} < 0.$$

Furthermore, from the first equation of system (3), it follows that $p_{31} > r_{13}$, so that variable V_1 is also suppressed.

If also $r_{13} = 0$, the borderline case of classical suppression appears.

Second, we will examine the case in which exogenous variable V_1 plays the role of suppressed variable. According to Conger (1974), it follows that $p_{31} > r_{13} > 0$. We now analyze the possible values for p_{32} and p_{21}. Here we only have to examine those cases in which p_{32} and p_{21} have a different sign:

(b′) $p_{31} > 0$, $p_{32} > 0$, and $p_{21} < 0$. This coincides with case *b*, the situation of *reciprocal* suppression. The correlation between V_1 and V_3 is now partially the consequence of a negative indirect effect. If, in addition, $r_{23} = 0$, then the borderline case of classical suppression appears.

(c) $p_{31} > 0$, $p_{32} < 0$, and $p_{21} > 0$. In this case, there is negative suppression. The correlation between V_1 and V_3 is partly the consequence of a negative indirect effect. As in the case for inequality (4a), it can be deduced for this situation that

$$r_{12} > \frac{r_{23}}{r_{13}}. \tag{4b}$$

V_2 is also a suppressed variable if $p_{32} < -r_{23}$. V_1 and V_2 are the suppressor and suppressed variable for each other. If also $r_{23} = 0$, then the classical variant of suppression occurs.

DIFFERENCES BETWEEN ANALYSES WITH AND WITHOUT LATENT VARIABLES

If possible, path analyses should be applied to latent theoretical concepts. These analyses entail the advantage that the intercorrelations of the latent concepts are corrected for attenuation as a consequence of measurement errors, because of which they are estimated higher than in models with only observed variables. The question is whether, with regard to the occurrence of the suppressor phenomenon, we can expect differences between analyses with and without latent variables. If ρ_{ii} is the reliability of variable X_i, the well-known formula for attenuation correction (McNemar 1969:172) can be imported into the inequalities (4a) and (4b). In the three-variable situation and the most prevalent case of negative suppression, this converts inequality (4a) into

$$\frac{r_{12}}{\rho_{22}} > \frac{r_{13}}{r_{23}}, \tag{5a}$$

if the explanatory variable V_2 plays the role of suppressed variable. Thus, the value of the left-hand term is increased inversely proportionally to the reliability of the suppressed variable, whereas the quotient in the right-hand term does not change. If variable V_1 plays the role of suppressed variable, inequality (4b) is applicable, which changes into

$$\frac{r_{12}}{\rho_{11}} > \frac{r_{23}}{r_{13}}. \tag{5b}$$

If an analysis with latent variables entails correction for measurement errors in the suppressed variable, the probability that a suppressor effect will appear increases.

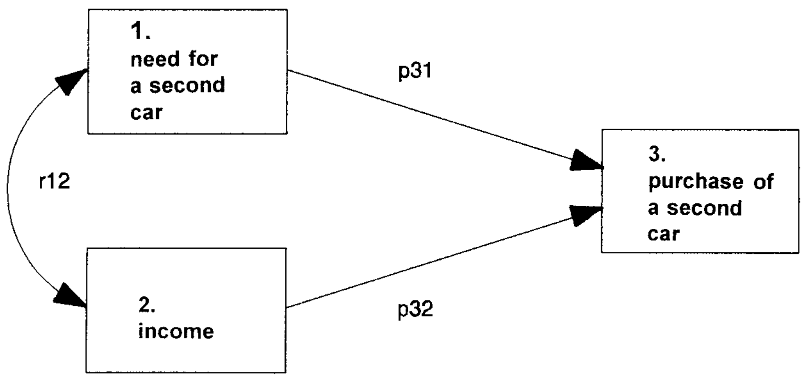

Figure 2: Path Model for Example: Purchase of a Second Car
SOURCE: Nie et al. (1975).

TABLE 2: Path Analysis Outcomes of the Example: Purchase of a Second Car (see Figure 2)

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
	r_{31}	r_{32}	r_{12}	$b_{31.2}$ =	$b_{32.1}$ =	$r^2_{3(1.2)}$	$r^2_{3(2.1)}$	$R^2_{3.12}$
	(r^2_{31})	(r^2_{32})		p_{31}	p_{32}			
V3 = purchase of a second car, *V1* = need for a second car, *V2* = income								
	.08	.55	–.32	.285	.641			
	(.006)	(.302)				.073	.369	.376

SUPPRESSING OR MASKING VARIABLE?

Related to the concept of suppressor variable is the concept of *masking variable*. We will illustrate this with a fictitious example borrowed from Nie et al. (1975:305). In the example, the *purchase of a second car* is the dependent variable, and the *need for a second car* and *income* are the independent variables. The central question is to what extent the purchase of a second car is influenced by the need for a new car, and one assumes of course a positive influence. The model and the data for this example are displayed in Figure 2 and Table 2, respectively.

The low correlation between need for a second car and purchase of a second car will amaze most people. However, if the variable *income* is included in the analysis, then the picture becomes clearer. The height of the income correlates positively with the purchase of a second car but appears to correlate negatively with the need for it. By including income in the analysis, the information in the need for a second car that *masks* the correlation with purchasing a second car is filtered out. The partial correlation between the need for a second car and the purchase of a second car is .32, after eliminating the differences in income. In algebraic terms, this example can be seen as a classical suppression situation or as a borderline case of reciprocal suppression. However, the variable that, from a classical perspective, would have been regarded as the suppressor is here—with respect to content—the most important explanatory variable, whereas the independent variable with the largest predictive validity plays the role of suppressor. It was probably this reversion that led Nie et al. (1975) to feel the need for a new term: *masking variable*.

EXAMPLES

EXAMPLE 1: OPINIONS ABOUT THE UNEMPLOYED

The first example is derived from a study of public opinion concerning the unemployed (Maassen and De Goede 1989, 1991). As part of this research, a model was tested for the factors that affect people's opinions of those out of work (Maassen 1997; Maassen and De Goede 1989). The complete model is displayed in Figure 3. The dependent variables in this model are two latent concepts: the respondents' perception of the vitality of the unemployed (*IMGVIT*) and their perception of the integrity of the unemployed (*IMGINT*). Both concepts are indicated by 12 items; 10 of these items have a substantial loading on the first concept and the other 2 items on the second concept. The model proposes that these two perceptions can be explained by three observed variables, assumed to be capable of being assessed without measurement error, and three latent concepts. The three variables first mentioned are as follows: age (*AGE*), educational level (*EDUCAT*), and a dichotomous variable (*NOWORK*) that indicates whether the respondent himself or herself is in receipt of a social benefit for being unemployed, either through redundancy or incapacitation. The three latent concepts are as follows: authoritarianism

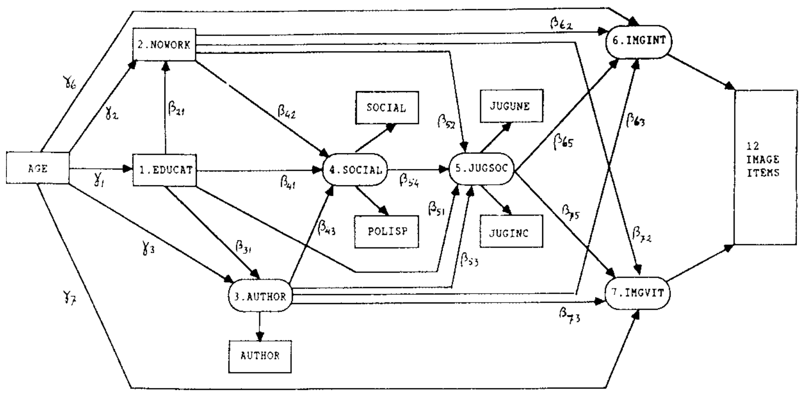

Figure 3: Path Model for Example 1: Opinions on the Unemployed

(*AUTHOR*), measured with a total score of seven items from Adorno's F-scale (Adorno et al. 1950); political preference (*SOCIAL*), indicated by two items; and evaluation of the quality of social services for jobless people (*JUGSOC*), also indicated by two items. For more details about the construction and properties of the model, see Maassen and De Goede (1989) and Maassen (1991, 1996, 1997).

For this example, we direct our attention to the mutual relationships between *AGE*, *AUTHOR*, and *IMGVIT*. The underlying hypotheses are the following:

1. With increasing age, individuals more strongly believe that citizens should conform to traditional norms. There exists a positive relationship between age and authoritarianism.
2. The more authoritarian one's attitude, the stronger the opinion that citizens should conform to traditional norms, particularly that one should support oneself through paid labor. In other words, there is a negative relationship between authoritarianism and opinion on the unemployed.
3. Following from Hypotheses 1 and 2: People hold more negative views on the unemployed as they get older.

This example can be regarded as representing an extensive class of opinion or attitude studies because, in path models for this type of research, most researchers would be inclined to include such variables as age and authoritarianism or comparable variables (e.g., rigidity or conservatism).

TABLE 3: Path Analysis Outcomes of Example 1: Opinions on the Unemployed

	Model With Only Observed Variables (Figure 1)				*Model With Latent Variables (Figure 3)*		
	1. AGE	*2.* AUTHOR	*3.* IMGVIT		*0.* Age	*3.* Author	*6.* Imgvit
AGE	—	*.317*	*.017*	*Age*	—	*.322*	*.177*
AUTHOR	.317	—	*–.426*	*Author*	.441	—	*–.653*
IMGVIT	–.118	–.421	—	*Imgvit*	–.114	–.601	—
r^2_{3i}	.014	.177		r^2_{6i}	.013	.361	
$r^2_{3(i.j)}$	.000	.164		$r^2_{6(i.jkl)}$	.025	.336	
$R^2_{3.12}$	.178			$R^2_{6.0235}$	.467		

NOTE: Correlations (below main diagonal) and path coefficients (above main diagonal) are shown in three-variable submodels with only observed variables (Figure 1) and with latent variables (Figure 3). Path coefficients are italicized.

For reasons of comparison, we also present the results of a strongly simplified analysis, in which the path model is limited to the variables *AGE*, *AUTHOR*, and *IMGVIT*. In addition, it is assumed that not only *AGE* but also *AUTHOR* and *IMGVIT* are assessed without measurement errors, using the total score of the 7 items from Adorno's F-scale and the total score of the 10 items indicating *IMGVIT* as alternative measures for *AUTHOR* and *IMGVIT*, respectively. The model is displayed in Figure 1, in which V_1 = *AGE*, V_2 = *AUTHOR*, and V_3 = *IMGVIT*. The correlations between these three variables can be found in the left-hand panel of Table 3 (below the diagonal). The estimates of the path coefficients resulting from classical path analysis can be found above the diagonal.

The right-hand panel of Table 3 presents the values of the correlations and the path coefficients of the three variables, estimated by a LISREL analysis of the model presented in Figure 3. As can be seen from this table, in both cases, the correlations between the three concepts are consistent with the hypotheses (i.e., the correlation between *AGE* and *IMGVIT* is negative). In the simple model, the value of the path coefficient between both variables is approximately 0 (nonsignificant: $t = .527$, $p = .598$), and the correlation between *AGE* and *IMGVIT* is wholly explained by the mediating variable *AUTHOR*.

The LISREL analysis for the full model yields $\chi^2 = 238.6$ with $df = 141$ ($p < .001$), which we regard as a satisfactory fit, taking into consideration the sample size ($N = 863$), the ratio of χ^2 and df (= 1.7), the fitted residuals, and the Q-plot. In this analysis, the path coefficient between *AGE* and *IMGVIT* even acquires a positive value. (The direct arrows between *AGE*, on one hand, and *IMGVIT* and *IMGINT*, on the other hand, are indispensable for the model. Deletion of these paths results in a significant deterioration of the fit: $\chi^2 = 24.7$, $df = 2$.) The pattern of the path coefficients conforms with situation *a* in the last section (which appears after rescaling *IMGVIT*). Thus, we see here negative suppression according to Conger's (1974) definition, where *AGE* plays the role of suppressor and *AUTHOR* that of suppressed variable. In contrast, according to Velicer's (1978) definition, *AGE* is the suppressor and suppressed variable, and *AUTHOR* is neither of these two.

Conclusions and interpretation. The analysis with only manifest variables and the analysis with latent concepts yield different results. In the former analysis, there is virtually no suppressor effect, whereas in the latter, a clear suppressor effect shows itself. This difference can be explained with the help of inequalities (4a) and (5a). In the second analysis, the relationships of the suppressed variable *AUTHOR* have been virtually corrected for measurement errors. Of course, we attach most value to the results of the analysis with latent concepts, and we will try to interpret only these results. Thus, *IMGVIT* is better explained by a linear composite of *AUTHOR* and *AGE* than by *AUTHOR* alone. In this linear composite, the path coefficients of *AGE* and *AUTHOR* are of opposite sign, whereas their zero-order correlations with *IMGVIT* are of the same sign. The sign of the coefficient of *AGE* switches in combination with the explanatory variable *AUTHOR*. It does not make sense to interpret the path coefficient of *AGE* as a direct effect in the strict sense. In an interpretation, *AGE* and *AUTHOR* should be combined as well. The finding that *AUTHOR* acts as a suppressed variable by inclusion of *AGE* can be substantively explained. If we wish to better understand the relationship between *AUTHOR* and *IMGVIT*, we have to eliminate the effect that respondents may score higher on authoritarianism only because of their age.

EXAMPLE 2: BURNOUT AMONG GENERAL PRACTITIONERS

The next example is a so-called 2W2V situation (two variables measured on two occasions) and has been derived from a study of burnout among 270 general practitioners (Bakker et al. 2000). At two moments (T1 = 1991 and T2 = 1996), their levels of job satisfaction and burnout have been assessed. The hypotheses underlying the path models are that in the short and long term, lack of job satisfaction causes burnout. In the long term, burnout causes a decrease in job satisfaction.

Thus, a negative relationship between job satisfaction and burnout is predicted. Earlier we had seen that positive zero-order correlations facilitate the analysis. Therefore, the satisfaction variables were rescaled such that they now indicate lack of job satisfaction. In this example too, for reasons of illustration, the data have been analyzed in different ways. In the most elaborated variant, both concepts are considered as latent variables, which are both measured by manifest variables. The latent concept of (lack of) job satisfaction will be denoted by *Sati*, measured by the indicators *SAT1i* and *SAT2i* (time points are indicated by $i = 1,2$). The latent concept burnout is denoted by *Boi*, assessed with the indicators *BO1i*, *BO2i*, and *BO3i*.[1] The modeling of the hypotheses is shown in Figure 5.

In addition, we present a simplified variant, in which the same hypotheses are tested but on the basis of a model that only includes (a selection of the) observed variables. In this case, it is assumed that (lack of) job satisfaction on both occasions is measured without error by the variables *SAT1i* (i.e., *SAT11* and *SAT12*); burnout is measured by the variables *BO1i* (i.e., *BO11* and *BO12*). Figure 4 shows how the hypotheses are modeled. The data and the results can be found in the matrix in the left panel of Table 5. The lower half of the matrix contains the correlations between the four variables, and the upper half contains the path coefficients (in italics). In addition, Table 5 presents the squared zero-order correlations, semipartial correlations, and multiple correlation coefficients.

In the more advanced variant (i.e., the model of Figure 5), the same model parameters have been estimated using the LISREL program. The outcomes are presented in the right-hand panel of Table 5. This analysis results in correlations and regression coefficients between

TABLE 4: Path Analysis Outcomes of Example 2: Burnout Among General Practitioners

	Model With Only Observed Variables (Figure 4)				*Model With Latent Variables (Figure 5)*		
	V_1 = SAT11, V_2 = BO11, V_4 = BO12				V_1 = Sat1, V_2 = Bo1, V_4 = Bo2		
	SAT11	BO11	BO12		Sat1	Bo1	Bo2
1. *SAT11*	—	*.478*	*.108*	1. *Sat1*	—	*.812*	*–.227*
2. *BO11*	.478	—	*.568*	2. *Bo1*	.812	—	*.880*
4. *BO12*	.379	.619	—	4. *Bo2*	.488	.696	—
r^2_{4i}	.144	.384		r^2_{4i}	.238	.484	
$r^2_{4(i.j)}$	.009	.249		$r^2_{4(i.j)}$	.017	.264	
$R^2_{4.ij}$	.393			$R^2_{4.ij}$	.501		
	V_1 = SAT11, V_3 = SAT12, V_4 = BO12				V_1 = Sat1, V_3 = Sat2, V_4 = Bo2		
	SAT11	SAT12	BO12		Sat1	Sat2	Bo2
1. *SAT11*	—	*.354*	*.214*	1. *Sat1*	—	*.496*	*.154*
3. *SAT12*	.354	—	*.469*	3. *Sat2*	.496	—	*.672*
4. *BO12*	.379	.544	—	4. *Bo2*	.488	.749	—
r^2_{4i}	.144	.296		r^2_{4i}	.238	.561	
$r^2_{4(i.j)}$	.040	.192		$r^2_{4(i.j)}$	.018	.341	
$R^2_{4.ij}$	.336			$R^2_{4.ij}$	.579		
	V_2 = BO11, V_3 = SAT12, V_4 = BO12				V_2 = Bo1, V_3 = Sat2, V_4 = Bo2		
	BO11	SAT12	BO12		Bo1	Sat2	Bo2
2. *BO11*	—	*.393*	*.479*	2. *Bo1*	—	*.476*	*.439*
3. *SAT12*	.393	—	*.356*	3. *Sat2*	.476	—	*.540*
4. *BO12*	.619	.544	—	4. *Bo2*	.696	.749	—
r^2_{4i}	.384	.296		r^2_{4i}	.484	.561	
$r^2_{4(i.j)}$	.195	.107		$r^2_{4(i.j)}$	.149	.225	
$R^2_{4.ij}$	.491			$R^2_{4.ij}$	.710		

NOTE: Correlations (below main diagonal) and path coefficients (above main diagonal) are shown in three-variable submodels with only observed variables (Figure 4) and with latent variables (Figure 5). Path coefficients are italicized.

TABLE 5: Path Analysis Outcomes in Example 2: Burnout Among General Practitioners

Model With Only Observed Variables (Figure 4)					*Model With Latent Variables (Figure 5)*				
	SAT11	BO11	SAT12	BO12		Sat1	Bo1	Sat2	Bo2
SAT11	—	*.478*	*.215*	*.033*	*Sat1*	—	*.812*	*.320*	*–.419*
BO11	.478	—	*.291*	*.466*	*Bo1*	.812	—	*.216*	*.751*
SAT12	.354	.393	—	*.349*	*Sat2*	.496	.476	—	*.599*
BO12	.379	.619	.544	—	*Bo2*	.488	.696	.749	—
r^2_{4i}	.144	.384	.296		r^2_{4i}	.238	.484	.561	
$r^2_{4(i.jk)}$	.001	.155	.098		$r^2_{4(i.jk)}$	.057	.188	.265	
$R^2_{4.123}$	.491				$R^2_{4.123}$	.767			

NOTE: Correlations (below main diagonal) and path coefficients (above main diagonal) are shown in the four-variable models with only observed variables (Figure 4) and with latent variables (Figure 5). Path coefficients are italicized.

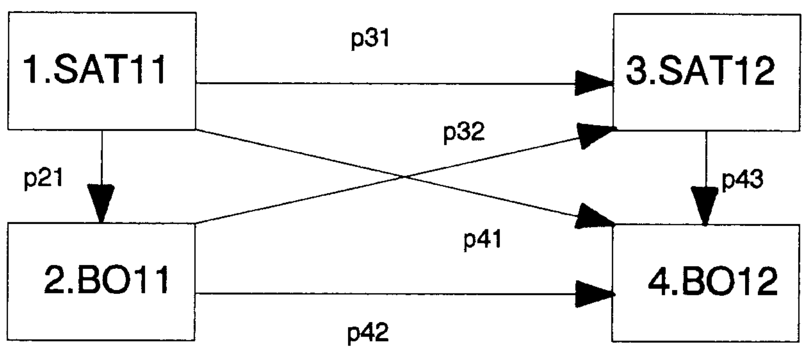

Figure 4: Path Model With Only Observed Variables for Example 2: Burnout Among General Practitioners

latent variables. Since they have been corrected for attenuation by measurement errors, they have higher values than the correlations or the regression coefficients in the left-hand panel of this table.

For comparison, additional analyses have been conducted in which the two variants are reduced to three-variable situations. In these analyses, burnout on T2 is the dependent variable, and two of the three other variables are explanatory variables. This leads to a total of six

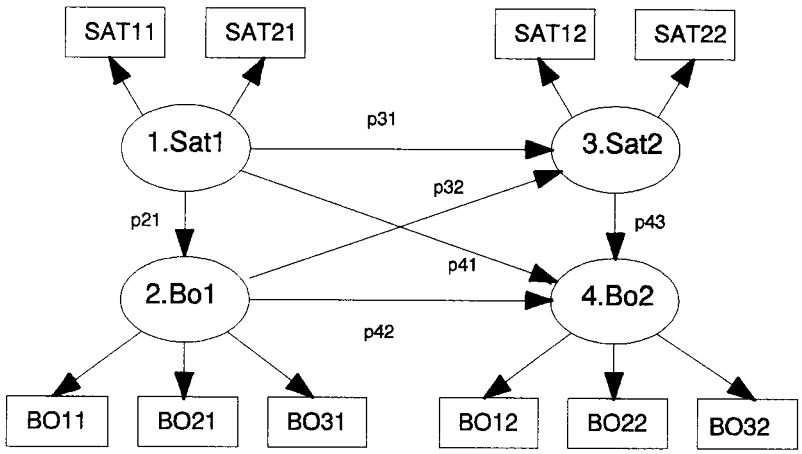

Figure 5: Path Model With Latent and Observed Variables for Example 2: Burnout Among General Practitioners

three-variable situations, the results for which are displayed in Table 4.

The central question is how burnout on T2 is influenced. We therefore concentrate on the results in Table 4 and in the last column of both panels of Table 5. In two out of eight situations, the suppressor phenomenon, according to Conger's (1974) definition, seems to occur: the three-variable situation with latent concepts, in which job satisfaction and burnout on T1 are the independent variables, and the four-variable situation with latent concepts. In these situations, the path coefficient between burnout on T1 and burnout on T2 is larger than its zero-order correlation. Furthermore, the sign of the path coefficient between satisfaction on T1 and burnout on T2 is opposite to the sign of the corresponding zero-order correlation coefficient. In both situations, we shall examine the composition of r'_{24} (according to the numeration of variables in Figures 4-5). In the three-variable situation, this leads to

$$r'_{24} = p_{42} + p_{41} \bullet r_{12} = .89 + -.22 \bullet .81 = .70.$$

We see a direct effect whose value is larger than the correlation and a negative effect as a consequence of a spurious relationship. This is situation *a* in the last section, the negative suppression situation. According to Conger (1974), job satisfaction at T1 is the suppressant for burnout at T1, but not vice versa, but if we take Velicer's (1978) definition, there appears to be no suppression at all. In the four-variable situation, the decomposition of effects (Pedhazur 1982:588) becomes as follows:

$$r'_{24} = p_{42} + p_{41} \bullet r_{12} + p_{43} \bullet p_{32} + p_{43} \bullet p_{31} \bullet r_{12} = .75 + -.34 + .13 + .16 = .70.$$

The correlation is composed of (1) a direct effect, of which the numerical value also exceeds the correlation; (2) a negative effect (as a consequence of a spurious relationship); (3) a positive indirect effect; and (4) a positive effect as a consequence of a spurious relationship.

In both cases, the negative effect is caused by a negative path coefficient for job satisfaction at T1. The correlation between satisfaction at T1 and the dependent variable is positive and substantial (.49), but the sign switches when the regression coefficient is calculated. The correlation is thus not high enough to warrant the (expected) positive direct effect. The variable measuring satisfaction at T1 contains information in common with the dependent variable, but less than the information that this independent variable has in common with the variable measuring burnout at T1, and is irrelevant for the dependent variable. Thus, the role of the suppressor variable is imposed on satisfaction at T1; apparently, we see here the negative suppressor phenomenon at work.

Interpretations. The result mentioned above was unexpected and inconsistent with the hypothesis when interpreted in terms of path coefficients. We should not conclude that there is a negative direct effect and that the opposite of the hypothesis ("lack of job satisfaction has a positive impact on burnout") is true. A more plausible interpretation is possible, particularly in the four-variable situation. Let us take a look at the following regression equation:

$$Bo2' = .75 \bullet Bo1 + .60 \bullet Sat2 - .42 \bullet Sat1.$$

Burnout at T1 and job satisfaction at T2 are good predictors for burnout at T2, but instead of adding only the latter variable, the explanation is optimized by adding a linear composite of both satisfaction variables. This linear composite indicates the change in job satisfaction between both occasions. The fact that the weights of both satisfaction variables are different in absolute value is no obstacle to interpreting this linear composite as an indicator of *change* in satisfaction. Note that variables constituting a raw difference score, after standardization, always receive different weights if their standard deviations are different. In the LISREL analysis, the latent satisfaction variables are standardized, and thus a difference in weights is not inconsistent with what might be expected.

One remarkable feature is the difference of interpretation that should be given to the results in the four-variable situation with only manifest variables. In the latter case, the regression equation is

$$BO12' = .47 \bullet BO11 + .35 \bullet SAT12 + .03 \bullet SAT11.$$

In this explanatory equation, satisfaction at T1 plays no role, not even that of a suppressor variable. From inequality (4a), we can understand the difference in results of both analyses. As a consequence of the correction for measurement errors in the suppressed variable(s), the probability of encountering the suppressor phenomenon is greatest in the analysis with latent concepts. Of course, most value should be attributed to the results of an analysis with latent variables.

The relation between change scores and suppressor variables has been previously discussed by Glasnapp (1984). His starting point was the question of how a correlation between a change score *X-Y* and a third variable *Z* should be calculated. Glasnapp advocates including both components of the change score as separate variables in a regression analysis. Given the assumption that the variables are scaled such that both zero-order correlations are positive, if a difference score is indeed a good predictor, the two variables will receive a regression weight of a different sign. Thus, a suppressor situation occurs. In general, not only the sign but also the value of both regression weights will differ. According to Glasnapp, this provides information about which variable is dominant in the linear composite. The assignment of equal regression weights (as occurs in a change score) omits this information. Moreover, the real change score is then a less than optimum predictor. Glasnapp (1984) ends his article by remarking, “Unfortunately, the literature indicates that the occurrence in data of suppression conditions of any magnitude is rare. This alone leads one to conclude that the search for highly meaningful change score composites as predictor or criterion variables will be unrewarding" (p. 866). In our example, we saw the opposite happening. We did not begin with a change score, but the analysis showed that a meaningful change composite (unexpectedly) provided the best explanation. Accordingly, our example showed the occurrence of negative suppression.

Negative suppression in a 2W2V situation, as in our example, should not be seen as a rare phenomenon. To demonstrate this, we first deduce a general formula for a four-variable situation with one dependent variable Y and three explanatory variables. We assume that for some reason, the researcher has categorized the three explanatory variables into two groups: variables P_1 and P_2, on one hand, and variable S, on the other hand. We also assume that all variables are standardized. In addition, we define $P = \beta_1 \bullet P_1 + \beta_2 \bullet P_2$, the linear composite of P_1 and P_2 that explains Y optimally in the regression of Y on P_1 and P_2; the accompanying multiple correlation coefficient $R_{y.12} = r_{Py}$. From inequality (4a), it follows that variable S is a suppressor variable in a negative suppression situation if

$$r_{sp} > \frac{r_{sy}}{R_{y.12}}. \qquad (6)$$

This inequality is applicable to our example if we define the following: $S = Sat1$, $P_1 = Bo1$, $P_2 = Sat2$, and $Y = Bo2$. Then, the right-hand term of inequality (6) is a ratio with a multiple correlation coefficient in the denominator that is certainly higher than the stability coefficient r_{1y}, as well as a correlation between two different variables that have been measured on different occasions in the numerator. In general, the right-hand term will be considerably less than 1. The left-hand term is a correlation of S and a linear composite of P_2 (the same variable measured at another moment) and P_1 (another variable measured at the same moment). Generally, S and P_2 will correlate relatively strongly, and if S and P_1 have a considerable correlation too, r_{sp} may take a substantial value. In these circumstances, the probability of a negative suppression situation showing up in a 2W2V model should be considered as high.

For the verification of inequality (6) in our example, first the linear composite of *Bo1* and *Sat2* that optimally explains *Bo2* is determined: $P = .44 \cdot Bo1 + .54 \cdot Sat2$, with a corresponding multiple correlation $r(P, Bo2) = .710^{1/2} = .843$. Furthermore, we calculate $r(Sat1, P) = .76$. Thus, according to inequality (6) (i.e., according to Conger 1974), in the regression of *Bo2* on *Sat1* and *P*, there will be negative suppression if $r(Sat1, P) > r(Sat1, Bo2)/r(P, Bo2)$. This is indeed the case since $.76 > .488/.843 = .58$.

Although this example counts more than two explanatory variables, with the help of Conger's (1974) definition, the suppression situation was easy to recognize. That is not always the case. Suppose that the stability coefficient of burnout is equal to .65 (instead of .749). Then, we find the following regression equations:

$$Bo2' = .61 \cdot Bo1 + .61 \cdot Sat2 - .31 \cdot Sat1,$$

$$Bo2'' = P = .38 \cdot Bo1 + .57 \cdot Sat2,$$

$$Bo2''' = .82 \cdot P,$$

$$Bo2'''' = .97 \cdot P - .21 \cdot Sat1.$$

It is striking that in the first equation, the sign of the path coefficient of *Sat1* is opposite to the sign of $r(Sat1, Bo2)$, but none of the other explanatory variables on their own plays the role of suppressed variable. However, the last two equations show that *Sat1* is a suppressor with respect to *P*, the linear composite of *Sat2* and *Bo1* that optimally explains *Bo2*. Only the switch of the sign draws attention to a possible suppressor situation.

Conclusions. On the basis of these observations, with respect to a model in which two variables *X* and *Y* are each measured on two occasions, we can conclude the following. When the synchronous correlation $r(X_1, Y_1)$ is relatively strong, there is a high probability of encountering a suppressor situation. A necessary condition for suppression is then that at least one of the cross-lagged correlations, $r(X_1, Y_2)$ or $r(X_2, Y_1)$, is considerably lower than the stability coefficients $r(X_1, X_2)$ and $r(Y_1, Y_2)$, which is often the case. The suppressor effect can be particularly prevalent in models with latent concepts. An explanatory variable that seems to be of substantive interest runs the risk of being forced into the role of suppressor variable. In such a situation, an interpretation in terms of change scores is plausible.

It is obvious that these observations are not limited to models with two waves and two variables. Our example is the simplest representative of a large class of multiwave models with two or more repeatedly measured variables in which the suppressor phenomenon occurs since, in some part of the model, the conditions discussed above are met.

SUMMARY AND DISCUSSION

DETERMINING SUPPRESSOR EFFECTS

A researcher who builds a path model will generally only include variables that are substantively meaningful. A variable is rarely chosen because it has the suppressor characteristic. Thus, when the suppressor phenomenon occurs in a path analysis, it is usually not anticipated. A variable expected to have explanatory value suddenly appears to play only the role of suppressor variable. The examples discussed earlier suggest that such situations are definitely not rare.

When the suppressor phenomenon occurs, seemingly miraculous outcomes appear with one or more variables: Suddenly, a regression coefficient receives a value much higher than or of an opposite sign to that expected. Researchers aware of the suppressor phenomenon will recognize this and generally will also be able to identify the variable that plays the role of suppressor, if necessary, with the help of their substantive research questions. We have seen that the state of affairs may be more complicated at the algebraic level. In Nie et al.'s (1975) example (see Table 2 and Figure 2), apart from the research question, more than one independent variable can claim the title of suppressor variable. Conger's (1974) and Velicer's (1978) definitions, which are phrased in algebraic terms, allow this deliberately.

Researchers unfamiliar with the suppressor phenomenon will probably not know what to do with it. As we can testify, an innocent researcher may even consider the data worthless and the results unpublishable. In any event, it would be helpful if a warning were attached to the computer output recommending that statistical experts be consulted. To this end, we need to answer the question of how a suppressor variable in path models should be defined. Which of the definitions mentioned above should be used as a starting point?

Closer examination of Tables 2 and 3 shows that Velicer's (1978) definition is applicable to Example 1 but not to the two suppressor situations of Example 2. In those situations, the semipartial correlations are not higher than the corresponding zero-order correlation coefficients. In contrast, Conger's (1974) definition is applicable to each of the situations that we have identified as suppressor situations. For three-variable situations (with a criterion *Y*, predictor *P*, and suppressor *S*), Tzelgov and Stern (1978) have described the conditions conforming to Conger's definition but not to Velicer's. Tzelgov and Stern consider this "a marginal situation in which *S* is a suppressor according to Conger, but fails to satisfy the intuitively reasonable demand that it increases the validity of *P*" (p. 333; notations adapted to the present text). The inequalities provided by Tzelgov and Stern will not be applied here, but instead we derive relations more appropriate for the 2W2V situation. Those relations will specify the values of r_{sp} that satisfy the condition for suppression occurrence according to Conger but not to Velicer.

Departing from a three-variable situation with dependent variable *Y* and explanatory variables *P* and *S*, we note that variable *S* is not a suppressor according to Velicer (1978) if

$$\frac{(r_{py} - r_{sp} \bullet r_{sy})^2}{1 - r_{sp}^2} < r_{py}^2.$$

Multiplication of both terms with $1 - r_{sp}^2$, elaboration of the square and isolation of r_{sp} lead to

$$r_{sp} < \frac{2 r_{py} r_{sy}}{r_{sy}^2 + r_{py}^2}.$$

We now define $k = r_{sy}/r_{py}$ and combine this result with inequality (4a). Thus, according to Conger (1974) but not to Velicer (1978), negative suppression occurs with variable *S* as the suppressor if the following inequalities are satisfied:

$$k < r_{sp} < \frac{2k}{k^2 + 1}, \text{ where } k = \frac{r_{sy}}{r_{py}}. \tag{7}$$

We now apply this result to the 2W2V model, which, in addition to suppressor variable *S*, includes two other explanatory variables: P_1 and P_2. If we define *P* as the linear composite of P_1 and P_2 that optimally explains *Y* (with multiple correlation coefficient $R_{y.12} = r_{py}$), then *S* is the suppressor according to Conger (1974) but not to Velicer (1978) if r_{sp} satisfies the inequalities (7), while now $k = r_{sy}/r_{py} = r_{sy}/R_{y.12}$. (Because in general $R_{y.12} > r_{1y}$, *k* will now be smaller than in the three-variable situation.) For example, for $k = 0.50$, the following limits hold: $0.50 < r_{sp} < 0.80$; for $k = 0.75$, $0.75 < r_{sp} < 0.96$. This shows that in a situation where suppression according to Conger occurs (i.e., when the left-hand inequality of (7) is satisfied), there is a wide range for r_{sp} where Velicer's condition is not met.

To illustrate, we apply inequalities (7) to the two suppression situations in our Example 2. In the three-variable situation, *Y* = *Bo2*, *P* = *Bo1*, and *S* = *Sat1*, which leads to .70 = .488/.696 < .812 < 2 • .701/ $(.701^2 + 1)$ = .94. In the four-variable situation, *Y* = *Bo2*, P_1 = *Bo1*, P_2 = *Sat2*, and *S* = *Sat1*, which leads to .58 = .488/.843 < .76 < 2 • .579/ $(.579^2 + 1)$ = .87. On the basis of these outcomes, we conclude that Conger's (1974) definition is and Velicer's (1978) definition is not applicable to an important category of cases that one would usually regard as a suppressor situation. It is understood that we have problems with Tzelgov and Stern's (1978) qualification of "a marginal situation."

In our view, Conger's (1974) definition is to be preferred. It is attractive because it is based on a comparison between zero-order correlations and path coefficients, which, of course, play a central role in structural equations analysis. Conger's definition can easily be transformed into a possible warning for suppressor situations in the computer output of a structural relations analysis. The definition is based on the designation of a suppressed variable. In a three-variable situation, this designation is relatively simple. The warning can be further specified on the basis of the cases distinguished and discussed earlier. The problem becomes complicated in situations with more than two explanatory variables in which the *suppressed* variable is hidden as a linear composite. If the suppressor is a simple variable, then Cohen and Cohen's (1975) variant of the definition of a suppressor situation is useful: If the explanatory variables are scaled such that the zero-order correlations with the dependent variable are positive, then suppression occurs when a path coefficient of an explanatory variable is (1) larger than its zero-order correlation with the dependent variable or (2) less than zero. The researcher is then warned by the negative path coefficient. Suppression when the *suppressor* variable is hidden as a linear composite that increases the explanatory power of another set of variables, a situation that we have not yet encountered, can probably only be discovered by comparing the regression coefficients of all linear composites of subsets of explanatory variables with the corresponding multiple correlation coefficients.

WHAT TO DO IN A SUPPRESSOR SITUATION?

Researchers who have ascertained (e.g., with help of Cohen and Cohen's 1975 definition) that the suppressor phenomenon is present in the structural equations model to be tested will generally not be happy with it. The interpretation of a classical or negative suppressor situation is found to be particularly problematic: One finds something contrary to expectation. In these cases, the suppressor variable is a variable that correlates substantially with another explanatory variable. The suppressor variable may substantially correlate with the dependent variable but also shares with the other explanatory variable much information that is irrelevant to the dependent variable. If the suppressor variable and the explanatory variable are substantively strongly related (e.g., conservatism and authoritarianism), then one can drop one of the two or both the variables for reasons of parsimony. In cases in which the variables are substantively different, for theoretical reasons, simply deleting a variable will not often be an option, as shown in the example of the relationship between job satisfaction and burnout. Analysis will then show that the hypotheses, when interpreted in terms of path coefficients, and the a priori theoretical model are (partially) incorrect. In addition to the initial model, the researcher will be inclined to present the results of an adjusted model that fits the data more closely. In the adjusted model, the suppressor variable and the dependent variable will be connected by a direct path, which is associated with a regression coefficient larger (or of opposite sign) than that expected. It is obvious that this finding should be accompanied with the explanation that the theoretical model was not retained because of the occurrence of a suppressor phenomenon.

Furthermore, in the examples discussed earlier, we noted that if a suppressor variable is involved, the interpretation of the effects of an independent variable on a dependent variable in a path model (Pedhazur 1982) requires reassessment. If a variable has been designated as the suppressor, and a path coefficient between this variable and the dependent variable has been found with a sign opposite to that hypothesized, one should not then conclude that a direct effect contrary to that expected is operating. A variable only appears as a suppressor in combination with one or more other explanatory variables. Thus, when interpreting the results, one should combine the suppressor and these other variables and try to interpret the resulting linear composite in a meaningful way. When a suppressor and another explanatory variable measure the same but at different times, an interpretation in terms of change may be meaningful.

NOTE

1. For reasons of clarity, the names of the variables have been adjusted and so differ from the names used in the referred article. The indicators for burnout are the three subscales from the Maslach Burnout Inventory (MBI) (Maslach and Jackson 1986): emotional exhaustion (eight items), depersonalizaton (five items), and reduced personal accomplishment (seven items). See Bakker et al. (2000) for a detailed description of these scales. The indicators for (lack of) job satisfaction are items from a self-developed scale. An example item is, "I really enjoy my work."

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