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ORIGINAL PAPER

A Rationale and Method for Examining Reasons for Linkages Among Adolescent Risk Behaviors

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Abstract A large volume of research has investigated interrelations among adolescent risk behaviors. Although several theoretical accounts have been proposed, researchers have not directly examined hypotheses for *why* risk behaviors are linked. In the present paper, a distinction is drawn between predictive factors that explain variance in risk behaviors and "linkage factors" which may provide an explanation for why risk behaviors are interrelated. The relevance of linkage factors to risk behavior research, theory, and practice is described. Further, a simple to use and easy to interpret analytic technique for exploring linkage-related issues is illustrated. Using this technique, hypotheses regarding the role of predictors in explaining linkages among risk behaviors can be tested directly. The proposed line of inquiry will provide valuable input for intervention efforts and theoretically relevant information concerning linkages among adolescent risk behaviors.

Keywords Adolescence · Risk behavior · Latent factors · Correlations · Research methods

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Adolescent involvement in "risk behaviors" such as substance use, delinquent acts, and sexual activity is the focus of a very large volume of research. One broad area of inquiry within this literature examines interrelations among various adolescent risk behaviors. Typically, involvement in one behavior is found to be positively associated with involvement in other risk behaviors. Several proposals have been made concerning *why* adolescent risk behaviors are interrelated. Researchers, however, have yet to systematically examine these accounts. Consequently, proposals remain largely speculative despite having important implications for theory, research, and interventions related to adolescent risk behavior involvement.

The goals of the present paper are to discuss what we believe to be the primary factors that have led to this state of affairs in risk behavior research and to provide a novel solution. First, we review how interrelations among adolescent risk behaviors are typically studied, discuss proposals for why risk behaviors are interrelated, and explain why such accounts matter to theory, research, and related intervention efforts. Second, we describe an aspect of structural equation modeling (SEM) related to the meaning of explaining variance in a latent risk behavior factor that is often misinterpreted by risk behavior researchers, but which has substantive implications. Third, we demonstrate a simple to use and easy to interpret method to directly examine hypotheses concerning *why* risk behaviors are linked. Fourth, we

propose a novel line of inquiry that constitutes an important nexus for adolescent risk behavior theory, research, and intervention efforts.

Interrelations among adolescent risk behaviors

Interrelations among adolescent risk behaviors are usually assessed in terms of correlations among self-report measures of risk behavior frequency and examined using factor analytic techniques. Following the seminal work by Jessor and Jessor (1977) on Problem Behavior Theory (PBT), researchers have explored how best to account for interrelations among adolescent risk behaviors. As summarized recently by Willoughby *et al*. (2004), when multiple risk behaviors are assessed in a single study, best-fitting factor models include typically separate latent factors for individual risk behaviors (e.g., substance use measures load onto one factor, and measures of delinquency load onto a different factor) as well as a higher-order latent factor accounting for the interrelations among the first-order factors.

Multiple explanations have been proposed for why risk behaviors are interrelated. According to Problem Behavior Theory (Jessor and Jessor, 1977; Jessor *et al*., 1991), a general tendency towards deviance or unconventionality leads youth to involvement in multiple risk behaviors. Stated differently, according to PBT, different risk behaviors are a manifestation of the same underlying tendency towards deviance. Other single-source influences also have been proposed, such as low self-control (e.g., Gottfredson and Hirschi, 1990). Zhang *et al*. (2002) proposed two primary influences, personal tendencies towards psychopathy and environmental opportunities, which interact to determine the specific nature of risk behavior involvement. Other investigators propose that associations among risk behaviors stem from multiple common sources. For example, in their integrative Theory of Triadic Influence (or TTI), Flay and colleagues (Flay and Petraitis, 1994; Petraitis *et al*., 1995) propose that multiple levels and types of influences are common to all health-related behaviors.

Others have proposed that interrelations among risk behaviors may remain even after controlling for common predictive factors since certain predictors may be unique to specific risk behaviors (e.g., Allen *et al*., 1994; Barnes *et al*., 2002; Elliot *et al*., 1985; Farrell *et al*., 2000; McGee and Newcomb, 1992; Osgood *et al*., 1988). Further, some risk behaviors may lead directly to other risk behaviors, independent of common influences. Alcohol use, for example, may lead to illicit drug use (Barnes *et al*., 2002; Kandel *et al*., 1992) and aggression may lead to substance use and delinquency (e.g., Farrell *et al*., 2005; Patterson *et al*., 1989). Some of the linkage among risk behaviors also may be a coincidental by-product of adolescent experimentation during the same time period (White, 1992). Most typically, researchers propose a middle-ground account in which some predictive factors are thought of as influencing a number of risk behaviors while others may be more specific to a given behavior.

The importance of understanding linkages among adolescent risk behaviors

The potential implications of this area of inquiry constitute a critical nexus for risk behavior research, theory, and prevention/intervention efforts. Direct tests of purported common predictive factors would provide important and novel information concerning the relative uniqueness (vs. interdependence) of these behaviors. Evidence could accumulate across studies concerning whether factors that predict several individual risk behaviors also account for the interrelations among these risk behaviors. Such information is relevant to the multiple theoretical propositions concerning sources of the links between risk behaviors. Although an enormous volume of investigations have focused on understanding individual risk behaviors, few studies have tested whether a given set of variables predicts a wide range of risk behaviors in the same study sample. As a result, collective knowledge concerning common predictive factors for a wide range of risk behaviors comes primarily from literature reviews in which correlates of individual risk behaviors are tabulated across studies (e.g., Hawkins *et al*., 1992; Petraitis *et al*., 1995).

Explaining interrelations among risk behaviors also has important practical implications. A better understanding of the interrelations among risk behaviors is critical in determining whether prevention and intervention efforts should focus on a common set of risk factors or be tailored to specific behaviors (e.g., Farrell *et al*., 2005; Welte *et al*., 2004). If factors that predict a given risk behavior are not the same as those that explain the connections among risk behaviors, then changing one behavior through an intervention aimed at a specific cause or a given risk behavior will not necessarily reduce the co-incidence of other risk behaviors. For example, adolescent attitudes towards risk-taking may predict both alcohol use and delinquent activity involvement. However, such attitudes may not explain the observed association between alcohol use and delinquency. That is, alcohol use and delinquency may not be linked because of attitudes towards risk-taking. In such a case, an intervention aimed at changing attitudes towards risk-taking may reduce the overall incidence of alcohol use and delinquency, but may not alter the co-occurrence of alcohol use and delinquency within individuals. Alternatively, if some factors explain the associations among risk behaviors, then interventions focused on changing such common factors may lead to reductions in the co-occurrence of multiple risk behaviors even if multiple behaviors are not directly targeted (Allen *et al*.,

1997; Ary *et al*., 1999; Fleming *et al*., 2004; Vitaro *et al*., 2002). For example, attitudes towards risk-taking may explain, at least in part, the connection between alcohol use and delinquent behavior. If so, then interventions aimed changing adolescents' attitudes may decrease the overall incidence of alcohol use and delinquency *as well as* reduce the co-occurrence of alcohol use and delinquency even if both risk behaviors are not directly targeted.

Although various explanations for the associations among adolescent risk behaviors have been proposed, few investigations have systematically and directly tested these alternatives. Rather than examining potential reasons for the connections among risk behaviors, investigators have focused instead on describing and explaining within and between-person differences in the nature and degree of risk behavior involvement. Such studies hold the promise of improving our understanding of the processes by which adolescents become involved in risk behaviors, the developmental nature of this involvement, and potential consequences. Yet explaining variation in risk behaviors does not provide explanations for the *covariation* among risk behaviors. In the next section, we consider this issue in more detail in the context of structural equation modeling (SEM), a commonly used approach in the study of adolescent risk behaviors.

Using SEM to model a latent risk behavior factor

Researchers examining adolescent behaviors often use SEM techniques to model a latent factor in order to capture the variance shared among multiple risk behavior measures (see Willoughby *et al*., 2004). Consider the case in which a researcher has assessed several risk behaviors in a sample of adolescents: past year frequency of delinquent activities, sexual activity, alcohol use, and marijuana use. Typically, measures of these risk behaviors are positively interrelated. Compared to those less involved in delinquent acts, for example, youth reporting greater involvement are also more likely to report more frequent sexual activity, alcohol use, and marijuana use. More generally, youth reporting more frequent involvement in any one of the risk behaviors are more likely to report more frequent involvement in each of the others.

Using SEM, a latent factor can be modeled to account for the interrelations among the measures. In this case, the latent factor represents a hypothesized common cause and each behavior is interpreted as an effect of the latent variable (Kline, 1998; Ullman and Bentler, 2003). Such an approach is consistent with Jessor's work on Problem Behavior Theory in which a latent factor with positive loadings for each risk behavior is interpreted as providing evidence of a "syndrome" in which youth involved in one form of risk behavior are more likely to be involved in each of the other forms (e.g., Jessor *et al*., 1991).

Note, however, that SEM analysis is based on the covariance among the study variables. Good statistical fit for a latent factor model implies that the model explains the *covariance* among study measures—regardless of how much variance the latent factor actually explains in an individual measure or set of measures (Kline, 1998; Ullman and Bentler, 2003). Even a model that explains little of the variance in a set of measures may provide a good fit to the covariation among the measures. Consequently, finding that a model explains a substantial portion of variance in a given study measure is not a necessary or sufficient condition for good statistical model fit. In contrast, a model must explain the covariation among a set of measures in order to provide good statistical fit (Kline, 1998). Finding that the model also explains a substantial amount of variance in each of the risk behavior measures is an indirect outcome of the latent factor model and secondary to the main finding that the model does a good job of accounting for the covariance among measures. As we discuss below, this has important implications for the interpretation of study results.

Researchers have used latent risk behavior factors as dependent measures in order to examine potential causes of adolescent risk behavior. Across studies a variety of predictors of a latent risk behavior factor have been examined including intrapersonal and personality factors, familial factors, and peer factors (Cooper *et al*., 2003; Duncan *et al*., 1998; Farrell *et al*., 2000; Farrell and Sullivan, 2000; Fergusson *et al*., 1996; Fleming *et al*., 2004; Garnier and Stein, 2002; Jackson *et al*., 2000; Newcomb and McGee, 1991; Patterson *et al*., 2000; Vitaro *et al*., 2001; Zhang *et al*., 2002). In such reports, predictors are modeled as having directional effects on the latent risk behavior factor and attention is given to the amount of variance in the latent factor explained by the predictor(s).

In a study by Cooper *et al*. (2003), for example, two facets of personality, poor impulse control and avoidant styles of coping, explained nearly 30% of the variance in a latent risk behavior factor spanning sexual activity, substance use, delinquency, and academic underachievement. Patterson *et al*. (2000) reported that over 50% of the variance in a latent factor representing growth in several risk behaviors (substance use, sexual activity, criminal activity) was explained by involvement with deviant peers. Other recent studies have used a similar analytic approach (e.g., Barrera *et al*., 2001; Cooper *et al*., 2003; Duncan *et al*., 2000; Farrell *et al*., 2000; Farrell and Sullivan, 2000; Fleming *et al*., 2004; Zhang *et al*., 2002).

In each of these studies, the covariance represented by a latent risk behavior factor was used as a dependent measure, and predictor variables were interpreted as potential influences on risk behavior. The actual percentage of variance in the individual risk behavior measures (as opposed to the latent factor) explained by the predictors, however, was not

reported. Further, results describing whether the predictors also accounted for the associations among the risk behaviors were not provided. Nonetheless, researchers modeling a latent risk behavior factor as a dependent measure have interpreted their findings as evidence for "common factors that underlie the behaviors" (Welte *et al*., 2004; p. 305), which "contribute to the development of a general pattern of [risk behavior involvement] among adolescents" (Duncan *et al*., 1998, p. 68), or for "the contribution of multiple plausible antecedents to the general propensity to engage in a range of risky or problematic behaviors" (Cooper *et al*., 2003, p. 391). Similar interpretations have been offered in other recent studies (e.g., Barrera *et al*., 2001; Duncan *et al*., 2000; Farrell *et al*., 2000; Farrell and Sullivan, 2000; Fleming *et al*., 2004; Patterson *et al*., 2000; Zhang *et al*., 2002). Yet as we discuss in the next section, a predictor need not necessarily account for the covariance between two risk behaviors just because it accounts for variance in each of the individual risk behaviors.

Common predictive factors vs. linkage factors

In the context of predicting adolescent risk behavior involvement, we propose that the role of a potential predictor (or set of predictors) can be three-fold. First, it might explain variance in an individual risk behavior. To the extent it does so, a predictor can be considered as a potential influence on that behavior. Second, the predictor might explain variance in a number of risk behaviors. To the extent that it does so, the predictor could be considered a common predictive factor, that is, a potential influence on multiple risk behaviors (e.g., Hawkins *et al*., 1992; Petraitis *et al*., 1995, 1998). Third, although infrequently addressed in risk behavior research, a predictor also may explain the covariance among a set of risk behaviors (e.g., Jackson *et al*., 2000; Vitaro *et al*., 2001). To the extent that this is so, it could be considered a "linkage factor", that is, a potential source for the association among risk behaviors. A variable must predict two risk behaviors (i.e., be a common predictive factor) if it is to also explain some of linkage between them. It is not a statistical necessity, however, that a variable which is a common predictive factor need also explain the linkage between those behaviors.

Consider the hypothetical situation depicted in Fig. 1(a). The circles depict the variability in the frequency of self-reported alcohol use (sum of areas A, B, and C) and marijuana use (sum of areas C, D, E) in an adolescent high school sample. Area C represents variance that is shared by both risk behaviors, that is, the covariation or linkage between risk behaviors. The box represents a predictor or set of variables that are thought to be common predictive factors to both risk behaviors. In this situation, the predictor explains

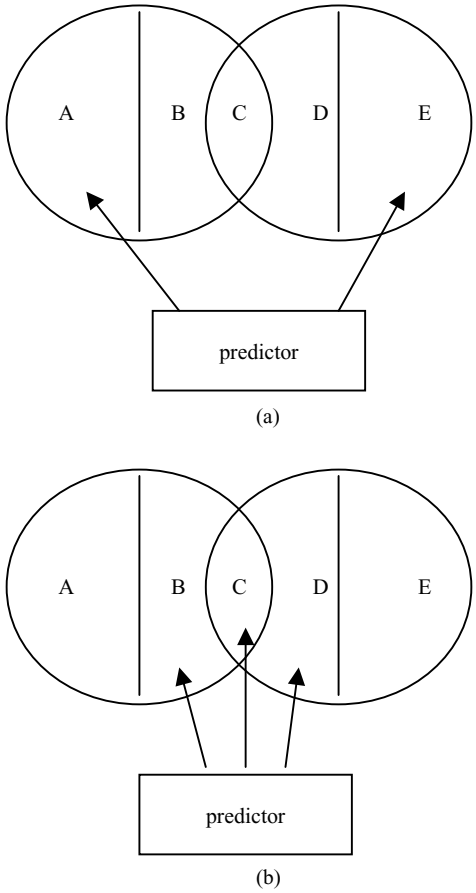

Fig. 1 (a) *Illustrating a common predictive factor.* Ovals represent the variance in two hypothetical risk behaviors. The box represents a hypothetical predictor. The lines indicate the variance in each risk behavior explained by the predictor. (b) *Illustrating a linkage factor.* Ovals represent the variance in two hypothetical risk behaviors. The box represents a hypothetical predictor. The lines indicate the variance in each risk behavior explained by the predictor

50% of the variance in alcohol use (area A) and 50% of the variance in marijuana use (area E). None of area C, however, is accounted for by the predictor. Even though this predictor is common to both alcohol and marijuana use, it does not explain the linkage between the risk behaviors. Thus, the linkage between the risk behaviors would not be diminished after controlling for the predictor.

In contrast, consider the situation presented in Fig. 1(b). The predictor set again explains 50% of the variance in alcohol use (areas B + C) and 50% of the variance in marijuana use (areas C + D). In this case, however, the explained variance also encompasses all of the variance that is common to both risk behaviors (area C). That is, the linkage between the risk behaviors is explained by the predictor. Thus, the predictive factor is common to both risk behaviors and it accounts for the linkage between the risk behaviors. In such a case, the predictor can be considered a potential common predictive factor for each risk behavior *and* a potential linkage factor.

Table 1 Summary of study measures

Variable	Measure	Items	Scale range	Alpha	Mean	SD
Risk behaviors	Alcohol – frequency	1	1 (never) to 8 (every day)	–	2.17	1.50
	Alcohol – amount	1	1 (less than 1) to 6 (10 + drinks)	–	2.60	1.74
	Marijuana use	1	1 (never) to 6 (every day)	–	2.17	1.61
	Sexual activity	3	1 (never) to 6 (every day)	.93	2.38	1.45
	Delinquency	4	1 (never) to 4 (more than 5 times)	.62	1.43	0.54
Risk behavior attitudes	Tolerance of deviance	11	1 (very wrong) to 4 (not at all wrong)	.89	1.97	0.56
	How risky for you	5	1 (very high) to 5 (very low)	.90	2.95	0.87
	How risky for others	5	1 (very high) to 5 (very low)	.92	2.79	0.84
	Parents would be upset	5	1 (very upset) to 4 (not at all)	.82	1.70	0.56
	Friends would be upset	5	1 (very upset) to 4 (not at all)	.90	2.78	0.81

Note. $N = 6758$.

Figure 1(a) and (b) are illustrative only. More realistic scenarios would likely involve a predictor (or set of predictors) which accounts for some of the variance in one or more risk behaviors and which accounts for some of the linkage. Yet, since a given predictor typically does not explain the majority of variance in a given risk behavior, even strongly associated risk behaviors may share variance that is unique from the predictor. That is, in terms of Fig. 1a and b, some of area C may not be accounted for by the predictor even among strongly associated risk behaviors. As a result, a predictor that is common to two risk behaviors may not *necessarily* account for the linkages between the risk behaviors. In the following section we illustrate these issues using actual data.

An empirical example

The empirical example described next is based on data from an on-going longitudinal study of adolescent lifestyle choices based on surveys of high school youth. Details of the study procedures and the risk behavior measures we refer to here are provided in Willoughby *et al*. (2004) and are summarized below.

The findings we report are for illustrative purposes only and substantive conclusions are not drawn. Illustrative results are based on the first wave of survey responses from 6758 students drawn from 25 high schools in a school district in Southern Ontario, Canada. Participants (49% male) ranged in age from 13 to 18 years ($M = 15.80$, $SD = 1.70$). The survey did not assess respondent race. However, consistent with the broader Canadian population (Statistics Canada, 2001), 91% were born in Canada and the most common ethnic background other than Canadian was British (18%), German (15%), French (13%), and Italian (11%). Data on socioeconomic status indicated mean levels of education for mothers and fathers falling between "some college, university or apprenticeship program" and "a college/apprenticeship/technical diploma". Respondents indicated that 94% of fathers and 82% of mothers had paying jobs at the time of the survey.

A 23 page self-report questionnaire was administered to students in classrooms by trained research staff. A total of two hours was allotted for survey administration at each school. Students were informed that their responses were completely confidential. The dataset includes measures of several adolescent risk behaviors including delinquent activities, sexual activity, alcohol use, and marijuana use. Details are provided in Table 1. Alcohol use was a composite of two items relating to frequency of drinking alcohol and typical number of drinks consumed; items were standardized and then averaged such that higher scores indicated greater alcohol use. Marijuana use was assessed using a single item based on past year frequency; higher scores indicated more frequent marijuana use. Sexual activity was a composite of three items (petting, oral sex, sexual intercourse) based on past year frequency; higher ratings indicated more frequent sexual activity. Delinquency was an aggregate of four items (sneaking out at night, shoplifting, joyriding, and wrecking other people's property) based on past year frequency; higher scores indicated more frequent delinquent activities. As shown in Table 2, measures of these risk behaviors were positively interrelated.

Figure 2(a) displays results from a latent factor analysis performed with AMOS software and maximum likelihood estimation using the illustrative data. In this model, four risk behavior measures (scores for delinquency, sexual activity, alcohol use, and marijuana use) were specified to have loadings on a latent risk behavior factor. To identify a scale of measurement for the latent factor, the unstandardized loading for marijuana use was fixed to 1.0. Residual variance terms also were specified for each of the four measured variables. Residual variances, the variance in the latent factor, and the magnitudes of the factor loadings were freely estimated (with the exception of the loading for marijuana use, as noted). No other parameters or constraints were specified in this model.

Table 2 Correlations among risk behaviours

Risk behavior	1	2	3	4
1. Delinquency	–			
2. Sexual activity	.44	–		
3. Alcohol use	.46	.54	–	
4. Marijuana use	.54	.56	.59	–

Note. $N = 6758$. All $ps < .001$.

Fit indices indicate that this model accounts for almost all of the covariance among the risk behavior measures (*CFI* = .99; *SRMR* = .01). Each of the risk behavior measures has a strong positive correlation with the latent variable as seen in the factor loadings (all $ps < .001$). Further, residual covariances among each pair of risk behavior measures not explained by the model were uniformly small (i.e., each less than .04 in standardized units). The model also explains substantial amounts of variance in each risk behavior, ranging from 42% for delinquency to 65% for marijuana use.

We then regressed the latent risk behavior factor onto a composite measure of self-reported risk behavior attitudes. In socio-cognitive theories such as the Theory of Reasoned Action and Theory of Planned Behavior (e.g. Azjen, 1988; Azjen and Fishbein, 1980), beliefs and expectations regarding outcomes and costs of a given behavior are expected to be the strongest immediate predictors of a behavior. Similarly, in the pan-theoretical framework of the Theory of Triadic Influence (e.g., Flay and Petraitis, 1994; Petraitis *et al*., 1995), attitudes and beliefs are expected to be among the most proximal causes of behavior and to serve as mediators for more distal influences. In the illustrative data, the attitudinal measure was a composite of five multi-item scales relating to expected social costs of risk behavior involvement (how upset friends would be; how upset parents would be), perceptions concerning the riskiness of the behavior (how risky for oneself and how risky for one's friends), and beliefs concerning how wrong various behaviors were (i.e., tolerance of deviance). Details are provided in Table 1. Scores for these five scales were reverse-scored, standardized, and then averaged to form a composite measure of risk behavior attitudes; higher values indicated more permissive attitudes towards risk behavior involvement.

In this latent variable regression model shown in Fig. 2(b), the four risk behavior measures (scores for delinquency, sexual activity, alcohol use, and marijuana use) were specified to have loadings on a latent risk behavior factor. As with the previous model, to identify a scale of measurement for the latent factor, the unstandardized loading for marijuana use was fixed to 1.0. and residual variance terms also were specified for each of the four measured variables. The composite risk behavior attitudes score was specified to have a directional path to the latent risk behavior variable. A residual variance term also was specified for the latent variable. Residual variances in the risk behavior measures and the latent risk behavior variable, the directional path from the predictor to the latent factor, and the factor loadings were freely estimated (with the exception of the loading for marijuana use). No other parameters or constraints were specified.

This model provided excellent fit to the sample data (CFI = .99; SRMR = .02). As shown in Fig. 2(b), the composite risk behavior attitudes measure had a strong relation with the latent risk behavior factor (standardized path coefficient = .72, $p < .001$), explaining 52% of the variance in the latent factor. One interpretation would be that the predictor, by explaining over half of the variance in the latent risk behavior factor, can be considered as a potential source of adolescent risk behaviors. That is, adolescents become more involved with risk behaviors such as delinquency, substance use, and sexual activity to the extent that they perceive fewer risks and costs associated with such behaviors. As we have seen, such an interpretation would be consistent with extant research and related theorizing.

But where in Fig. 2(b) is an indication of the amount of variance in the risk behaviors explained by the predictor? Recall that in a SEM model, the latent factor represents the *covariance*, or linkages among the behaviors, not the variance in the risk behaviors themselves. The results presented in Fig. 2(b) indicate that 52% of the covariance among the four risk behavior measures is accounted for by the predictor variable. No where in the model is there a direct indication of the amount of variance in a given risk behavior that is explained by the attitudes predictor variable. This information is *not* reflected by the amount of variance explained in the latent factor (i.e., 52%). Further, this information is also *not* reflected in the amounts of variance in the individual risk behavior measures explained by the latent factor (i.e., 44%, 50%, 53%, and 64%).

In contrast, consider the model presented in Fig. 2(c). There is no latent variable in this model. Instead, the composite risk behavior attitudes score was specified to directly influence each of the four risk behavior measures (scores for delinquency, sexual activity, alcohol use, and marijuana use). Residual variance terms were specified for each of the four measured variables. Further, correlations were specified between each pair of residual variance terms. These correlations are analogous to partial correlations and reflect the variance shared between risk behaviors after accounting for the predictive effect of the attitudinal measure. The directional paths from the predictor to the risk behavior measures, the residual variances, the variance in the predictor measure, and the correlations among the residuals were freely estimated. No other parameters or constraints were specified.

This model was 'just identified', that is, there were no extra degrees of freedom; consequently, it provided a perfect fit to the sample data (Kline, 1998). As shown in Fig. 2(c),

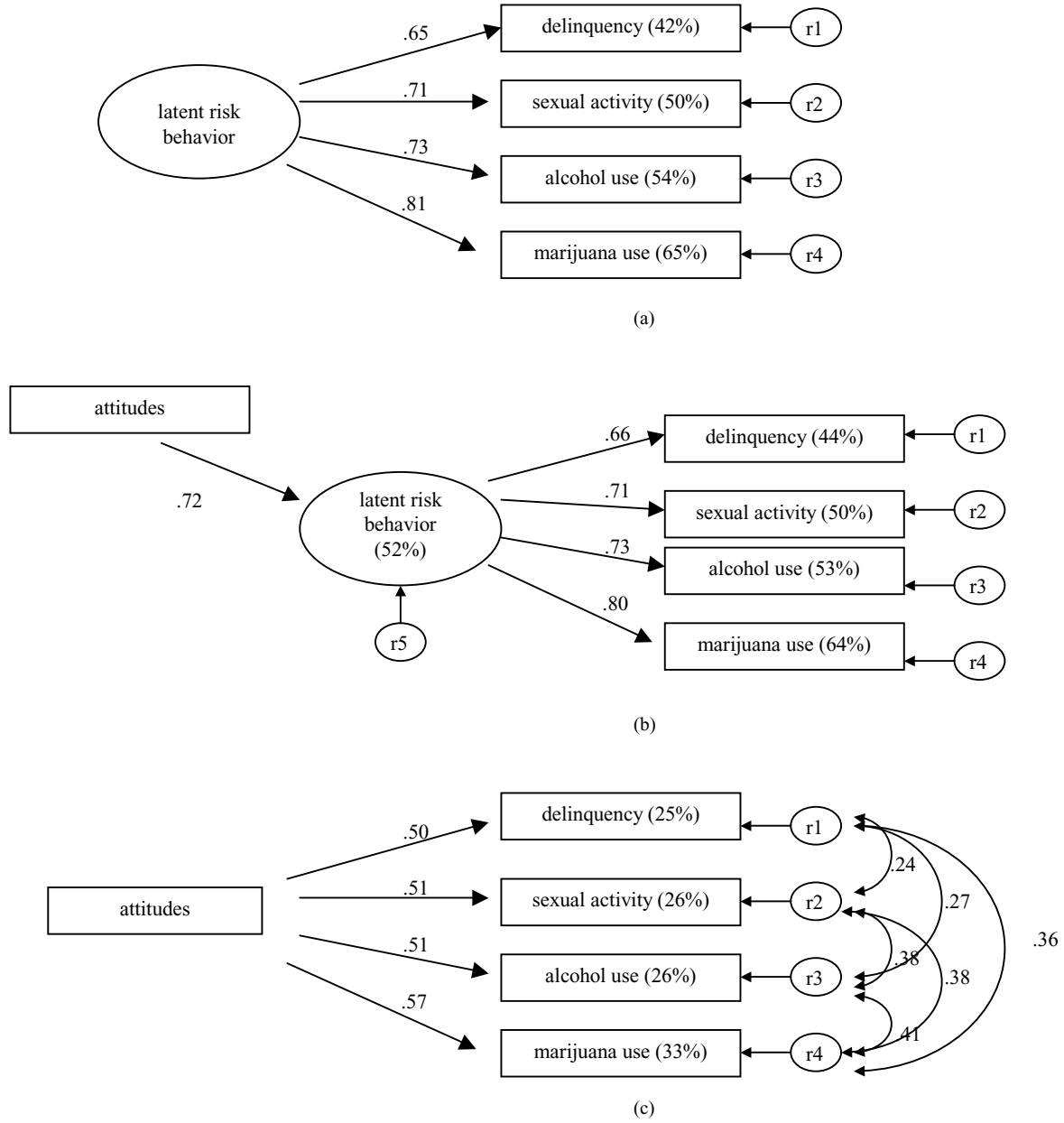

Fig. 2 (a) *A latent risk behavior factor using SEM*. Measured variables are shown in boxes. The oval represents a latent variable. The proportions of variance in each risk behavior measure explained by the latent variable are shown in parentheses. Factor loading of each measure on the latent variable are also shown. (b) *Predicting the latent risk behavior factor*. Measured variables are shown in boxes. The oval represents a latent variable. The proportions of variance in each risk behavior measure explained by the latent variable are shown in parentheses. Factor loading of each measure on the latent variable are also shown. The standardized path coefficient between the predictor and the latent risk behavior variable is shown as is the proportion of variance in the latent factor explained by the predictor (in parentheses). (c) *Regression of individual risk behaviors on the predictor.* Measured variables are shown in boxes. The proportions of variance in each risk behavior measure explained by the predictor are shown in parentheses. Correlations between risk behaviors are shown after controlling for the predictor

the residual variances in the risk behavior measures were positively intercorrelated after accounting for the common predictor. Also shown are the standardized path coefficients (all $ps < .001$) from the predictor to each risk behavior and the proportion of variance explained in each risk behavior by the attitudinal measure. The analysis shown in Fig. 2(c) provides direct information concerning the amount of variance explained in a given risk behavior by a predictor. The predictor explains between 25% and 33% of the variance in the individual risk behaviors. It also illustrates clearly that the attitudes predictor does *not* explain 52% of the variance in risk behavior, which begs the question, where does the

52% shown in Fig. 2(b) come from? In the next section we provide an answer to this question and we present a simple technique that can be used to examine linkage-related issues directly.

A method to examine linkages among risk behaviors

As noted above, the correlations among the residuals from each risk behavior shown in Fig. 2(c) are partial correlations, representing associations among risk behaviors that are independent of the predictor (Pedhauzer, 1973; Kline, 1995). Squaring these numbers (equivalent to squaring a partial correlation coefficient) yields the proportion of covariance between each pair of risk behaviors that remains after accounting for the predictor. These squared values can be compared to the squares of the zero-order correlation coefficients between risk behaviors (MacKinnon *et al*., 2000; Olkin and Finn, 1995). That is, as shown in Table 3, the reduction in the amount of covariance can be assessed by comparing r^2s and partial r^2s. The proportional reductions in the amount of covariance before and after accounting for the predictor reflects the amount of linkage among risk behaviors accounted for by the predictor. For example, the correlation between delinquency and sexual activity was .44 before controlling for the predictor and .24 after controlling for the predictor. The proportions of covariance, therefore, were 19% and 6% before and after controlling for the predictor. Consequently, the proportion reduction in covariance can be derived as: $[(.19 - .06)/.19]^*100 = 68\%$. That is, 68% of the linkage between delinquency and sexual activity measures can be accounted for by the attitudes predictor.

As shown in the last column of Table 3, the predictor accounts for between 51% and 68% of the linkage among pairs of risk behaviors. The median proportional reduction across the seven pairs is 55% which is consistent with the 52% of the variance explained in the latent risk behavior factor shown in Fig. 2(b). Unlike the latent factor approach, however, the linkage analysis in Table 3 clearly shows (1) the degree of shared variance between each pair of risk behaviors, (2) degree of shared variance between each pair of risk behaviors after accounting for the predictor, and (3) the reduction in the degree of linkage among each pair of risk behaviors after controlling for the predictor.

Table 3 Results from a linkage analysis

Risk behavior pair	r	r^2	pr	pr^2	% redux
Delinquency and sexual activity	.44	.19	.24	.06	68%
Delinquency and alcohol use	.46	.21	.27	.07	67%
Delinquency and marijuana use	.54	.29	.36	.13	55%
Sexual activity and alcohol use	.54	.29	.38	.14	52%
Sexual activity and marijuana use	.56	.31	.38	.14	55%
Alcohol use and marijuana use	.59	.35	.41	.17	51%

Note. $N = 6758$. All $ps < .001$ for correlations and partial correlations.

Importantly, all of this information can be estimated using standard statistical techniques in familiar packages such as SPSS. For example, the degree of shared variance between pairs of risk behaviors can be estimated by squaring the bivariate correlations derived from a correlation matrix. The degree of shared variance between pairs of risk behaviors after accounting for a predictor can be estimated by squaring the partial correlations derived from a partial correlation analysis in which the predictor variable serves as the covariate or control variable. Alternatively, each of the risk behaviors could be regressed onto the predictor in four separate regression analyses, the residuals from each of these analyses could be saved, then the residuals could be correlated and these correlations could be squared. The reduction in the degree of linkage among pairs of risk behaviors could then be estimated as outlined above.

None of this information is provided in the standard latent factor model in Fig. 2(b). Instead, only an estimate of the overall degree of linkage reduction (52%) is inferable from the results presented in the latent variable model. In order to make a correct inference concerning linkage reduction, however, researchers need to avoid (mis)interpreting the 52% as an indication of the amount of variance in "risk behavior" explained by the predictor. As we discussed above, in recent empirical work using SEM and latent risk behavior factors, however, it seems that researchers are frequently unaware of this distinction.

Other recent studies not based on SEM also illustrate this point. For example, Vitaro *et al*. (2001) hypothesized that gambling, delinquency, and substance use, "would develop in parallel from common roots and their links would be spurious (i.e., they would disappear or at least be substantially reduced once the common risk factors were controlled for)" (p. 173). Correlations among risk behaviors were examined before and after controlling for a set of expected common risk factors including impulsivity, peer deviancy, parental supervision, and socioeconomic variables. Between 3% and 18% of the variance in the individual risk behaviors was explained by the predictor set and correlations among risk behaviors were partially attenuated after controlling for the predictor set. The authors concluded that the predictors, "do not seem to account for a significant portion of the variance shared by these three problem behaviors" (p. 188). Not noted, however, was the fact that the linkage among pairs of risk behaviors was actually reduced between 40% and 58%

after controlling for the predictor set. Jackson *et al*. (2000) found that the correlation between alcohol and cigarette use was reduced after the effects of several variables (e.g., negative affectivity and substance use expectancies) were statistically controlled. The authors suggested that these predictors may, "have a common influence on the development of alcohol and tobacco use disorders (p. 685)." Not noted by the authors, however, was that the finding that the linkage reduction between alcohol and tobacco use was 51%, based on a comparison between the squared zero-order and partial correlations (correlations were .37 vs. .26 respectively).

Based on a comparison of correlations and partial correlations provided in a study by Garnier and Stein (2002), 65% of the linkage between teen drug use and delinquency was accounted for in a predictive model for peer drug use and delinquency. Instead of commenting on this finding, however, results were interpreted by the authors in terms of the predictive effects of family and peer domains on the development of the individual risk behaviors. Furthermore, Bryan and Stallings (2002) examined three facets of personality (harm avoidance, novelty seeking, reward dependence) as predictors of three adolescent risk behaviors (sexual activity, conduct disorder, substance use) in two samples of adolescent boys. Modest predictive relations between personality facets and risk behaviors were found in both samples. Not noted by the authors, but evident from the results reported in the study, was the finding that the linkages among the risk behaviors were only minimally reduced (less than 20%) after controlling for the predictors.

Thus, even in studies where the key elements of a linkage analysis are reported (i.e., correlations among risk behaviors before and after controlling for hypothesized predictors), emphasis is given to variance explained in the risk behaviors. Consequently, researchers have yet to examine directly and systematically which factors may jointly predict multiple risk behaviors and explain the linkages between those behaviors. In the next section, we propose a novel line of risk behavior inquiry to directly address this gap in the research literature.

Proposals for research on linkage factors

In order to advance our understanding of why adolescent risk behaviors are interrelated, we propose that explanatory factors need to be evaluated in terms of whether they predict individual risk behaviors *and* account for the linkages among risk behaviors. Affirmative evidence for both criteria would indicate that such predictors could be considered possible common predictive factors and possible sources of the linkages among multiple risk behaviors, that is, potential linkage factors. In studies using latent variables as dependent measures, we propose that researchers report the variance explained in individual risk behaviors, regardless of how much variance is explained in the latent factor. Such information speaks directly to whether the predictors explain variance in multiple risk behaviors. Further, regardless of whether SEM techniques are used, linkage analysis can be facilitated if researchers report correlations among risk behaviors before and after controlling for the predictors. Doing so systematically would allow information to accumulate across studies. Using the simple method we have illustrated based on the familiar elements of correlations and partial correlations, researchers also can consider re-examining already published results in order to determine whether evidence of linkage factors exists within existing datasets. Relatedly, intervention and prevention programs can be evaluated not only in terms of whether they reduce risk behavior involvement, but also in terms of whether they impact linkages among risk behaviors. Even if multiple risk behaviors are not targeted, such a pattern would suggest that the intervention impacted a linkage factor and thereby reduced both the incidence of the focal risk behavior(s) *as well as* the co-occurrence of that behavior with other risk behaviors.

As we have illustrated, the linkage reduction technique is a simple method for testing hypotheses about *why* risk behaviors are linked. The comparison of the amount of shared variance (r^2 vs. pr^2) provides a familiar and readily interpretable index well-suited for the present purposes. It does not necessarily involve sophisticated statistical software or large sample sizes typically required for SEM analysis. Instead, as we have detailed above, it is an accessible method that can be applied using a common statistical package such as SPSS. It is flexible in terms of the number of risk behaviors and the number of predictors examined. Further, it provides information specific to each pair of risk behaviors. Consequently, this technique provides a valuable supplement to more typical analytic techniques, such as factor analysis and structural equation modeling. As we have noted, this simple procedure can be applied to directly address proposals concerning why adolescent risk behaviors are linked. Importantly, any variable that one anticipates will be relevant to understanding why risk behaviors are linked can be incorporated using the method outlined above. Thus, if a researcher hypothesizes that some of linkage among a set of risk behaviors was directly related to socioeconomic factors, gender, pubertal status, and age, then the linkages among risk behaviors could be estimated before and after accounting for these factors either individually or collectively. Such work will provide novel and timely information relevant to risk behavior theory and related practice. Taking the study by Jackson *et al*. (2002) as an example, it may be that negative affectivity and expectations regarding the effects of substance use leads to severe alcohol, tobacco use, and the co-occurrence of the two. If so, then intervention efforts aimed at addressing global affective responses and substance-related expectancies would reduce not only the incidence of alcohol

and tobacco use, but also reduce the co-occurrence of these two disorders.

Several conceptual and statistical caveats are in order. First, identification of possible linkage factors which statistically account for shared variance among risk behaviors does not provide a substantive explanation for that shared variance. Longitudinal designs are required for testing whether predictors assessed at one time can explain linkages among risk behaviors at a later time, as well as linkages among changes in risk behaviors involvement over time. Also necessary are controlled intervention studies in which purported linkage factors are manipulated and the resulting impact on risk behavior involvement and interrelations among risk behaviors is assessed. Process-oriented research following the developmental course of individual youth and micro-level analysis of their decisions and behaviors also would provide valuable information concerning the reasons for co-occurrence of risk behaviors that cannot be captured through correlations and covariance estimates.

Second, although infrequently applied by risk behavior researchers, estimating the extent to which a third variable explains an observed relation between two other variables has been discussed for some time among methodologists (e.g., Pedhauzer, 1973). Further, several descriptive and inferential approaches to determining the extent to which a relation is diminished after controlling for an expected common influence have been presented (e.g., MacKinnon *et al*., 2002; Olkin and Finn, 1995). This methodological work, however, has assumed only a single common influence. Olkin and Finn (1995), for example, provided formulas to calculate confidence intervals around the difference between a simple correlation and a partial correlation for the case involving a single third-variable. Computational formulas and estimates of standard errors for the difference between *r*s and partial *r*s in cases where multiple common linkage factors are considered simultaneously are less widely available (MacKinnon *et al*., 2002). Consequently, *p*-values for the reduction in linkage as we have described it are not easily derived—particularly in cases where multiple linkage factors are considered. However, as in the case of other effect sizes such as the proportion of explained variance (e.g., r^2) or the standardized difference between two means (e.g., Cohen's *d*), in many situations a simple summary of the reduction in linkage before and after controlling for hypothesized linkage factors will be an important piece of descriptive information even if an inferential test (and associated *p*-value) is not readily available (Wilkinson *et al*., 1999).

These limitations notwithstanding, the method we have illustrated provides a valuable first step to directly exploring linkage-related issues. Squaring correlations to yield estimates of the degree of shared variance before and after controlling for a common linkage factor provides a readily interpretable metric to judge the extent to which the overlap between pairs of risk behaviors is diminished after controlling for an expected linkage factor (or factors). Although discussion of related statistical tests have appeared in methodological sources (e.g., Pedhauzer, 1973; MacKinnon *et al*., 2002; Olkin and Finn, 1995), application to linkages among adolescent risk behaviors has not been made. Yet by using this analytic technique as a supplement to more commonly applied analyses, specific hypotheses regarding the role of predictors in explaining linkages between adolescent risk behaviors can be tested directly. For these reasons, we believe that the technique deserves to be applied by risk behavior researchers more broadly. Collectively, this area of research will produce much needed input for intervention efforts and provide valuable theoretical as well as empirical information concerning linkages among adolescent risk behaviors.

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