Using Log-Linear Models for Longitudinal Data to Test Alternative Explanations for Stage-Like Phenomena: An Example from Research on Adolescent Substance Use

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We show how log-linear models for multi-wave longitudinal data can be used to test hypotheses relating to stage-like relationships between variables. To illustrate our approach, we use an example from research on adolescent cigarette and marijuana experimentation. Previous research has documented that most adolescents experiment with substances in a stage-like sequence: first cigarettes and then marijuana. Several hypotheses have been suggested as potential explanations for this stage-like phenomenon. We show that traditional two-wave analyses give results that are difficult to interpret and that our multiple-wave analyses allow the testing of several theoretically interesting hypotheses. We also illustrate that log-linear models may be useful for testing hypotheses about stage-like phenomena in many other areas of psychological research. We suggest how several other techniques have the potential to be used as a multivariate analogue to the log-linear approach.

Log-linear models have been widely used in the analysis of longitudinal data. One approach that involves the analysis of square contingency tables was first popularized in sociology by Goodman (1969; 1971; 1978; 1979), although the roots of the approach can be traced back even further (e.g., Deming & Stephan, 1940). The purpose of the current article is to show how log-linear models for square contingency tables can test hypotheses about stage-like phenomena in longitudinal psychological research. Although stage theories and stage-like phenomena are present in many areas

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of psychological research (Baumrind, 1985), there have been no examples in longitudinal psychological research of the use of log-linear models for square contingency tables. For the current article, we illustrate the utility of this approach by testing several theoretically interesting hypotheses regarding the stage-like relationship between the initiation of adolescent cigarette and marijuana use.

Previous Theoretical Explanations for the Stage-Like Progression of Adolescent Substance Use

The Gateway Hypothesis

Previous research has documented that most adolescents begin to experiment with substances in a stage-like sequence or order: first alcohol and cigarettes, then marijuana and finally hard drugs. For a review, see Kandel (1989). Attempts to explain the stage-like progression have stimulated considerable controversy (e.g., Baumrind, 1983; Hays, Widaman, DiMatteo & Stacy, 1987; Huba, & Bentler, 1982; Martin 1982; Miller, 1994; O’Donnel & Clayton, 1982).

One plausible explanation for the stage-like progression is that cigarette smokers are at increased risk for experimenting with marijuana. This hypothesis has been referred to as the “gateway hypothesis” (Kandel & Faust, 1975). The stepping stone, gateway or stage hypothesis has received considerable attention from both researchers and the popular press (see Baumrind, 1983; Cohen, 1972; Kandel, 1989; Martin, 1982; Miller, 1994; O’Donnel & Clayton, 1982). Cohen (1972) attributed the gateway hypothesis to New York City police officers in the 1940’s. These police officers believed that people who experiment with marijuana inevitably become heroin addicts. The gateway hypothesis argues that people who use soft drugs (e.g., marijuana) are more likely to progress to the use of harder drugs (e.g., amphetamines, barbiturates, heroin). In addition, the gateway hypothesis argues that using cigarettes and alcohol is a “necessary but insufficient condition for the use of higher order drugs” such as marijuana and hard drugs (Kandel, 1989).

Substance use researchers have experienced problems testing this hypothesis using traditional statistical methods. For example, no statistical analyses were performed in the first three longitudinal studies that attempted to examine the relationship between initial cigarette and marijuana use (Coombs, Fawzy & Gerber, 1986; Fillmore, 1975; Kandel & Faust, 1975). These researchers simply showed that most subjects experimented with cigarettes before marijuana. In recent years, two studies used longitudinal
Guttman scaling to illustrate that smoking, marijuana use and other substance use followed a prescribed Guttman scale (Ellickson, Hays & Bell, 1992; Kandel, Yamaguchi & Chen, 1992).

The Problem Behavior Hypothesis

Problem behavior theory argues that some adolescents develop a problem orientation that predisposes them to experiment with all types of substances and engage in other delinquent behaviors (Jessor & Jessor, 1977). For example, adolescents who begin to use cigarettes are expected to begin to experiment with other substances (e.g., marijuana) and engage in other problem behaviors. Jessor and Jessor suggest that problem behaviors are age related and that the initiation of problem behaviors marks a transition to a problem behavior orientation.

Problem behavior theory may be a partial explanation for the stage-like progression that occurs in substance use research. Two groups of adolescents that represent two stages are hypothesized by problem behavior theory: (a) a healthy group of adolescents who are not willing to use any substances are referred to by Jessor, Donovan and Costa (1991, p. 25) as the “nonproblem behavior or conventional behavior group” and (b) a “problem prone” group of adolescents who are willing to use all types of substances (Jessor & Jessor, 1977). For this article, the hypothesis that there is a group of adolescents who are not willing to use any substance is referred to as the “healthy group hypothesis.” The “problem behavior group” refers to the subgroup of adolescents who are willing to use all types of substances. According to problem behavior theory, cigarette smoking is predictive of marijuana use because cigarette users are willing to use marijuana. For this reason, problem behavior theory suggests that many adolescents begin to use both substances at the same time. In addition, adolescents who do not use marijuana and cigarettes are hypothesized to be part of a healthy group of adolescents who are unwilling to use either substance.

Previous longitudinal research has not attempted to determine whether the onset of cigarette and marijuana use is more likely to occur at the same time. We will show that log-linear models can test this hypothesis as well as the problem behavior and healthy group hypotheses.

The Statistical Independence Hypothesis

The gateway and problem behavior hypotheses suggest that the stage-like phenomenon is produced by a statistical association between cigarette and marijuana use. However, the stage-like phenomenon can occur even if
the times of initiation of cigarettes and marijuana are independent processes. Hamburg, Kraemer and Jahnke (1975) suggest that the stage-like progression may not be produced by an association between different rates of substance use and may reflect an artifact produced by two statistically independent processes. For example, cigarettes are more widely used and used at earlier ages than marijuana. Therefore, more adolescents may use cigarettes before marijuana because the average adolescent uses cigarettes at earlier ages than the average adolescent who experiments with marijuana. In this case, most adolescents would use cigarettes before marijuana even if the use of cigarettes was not correlated with marijuana use. According to this hypothesis, the stage-like progression is not produced by a statistical association between cigarette and marijuana use. We refer to this hypothesis as the "statistical independence" hypothesis.

Prior longitudinal research has documented that cigarette and marijuana use are predictive of one another (e.g., Collins, Graham, Long & Hansen, 1994; Ellickson, Hays & Bell, 1992; Newcomb & Bentler, 1986). Therefore, cigarette and marijuana use are not entirely independent processes. However, prior research has not attempted to sort out the relative extent to which independent and correlated processes determine the stage-like phenomenon (Miller, 1994).

Statistical Issues

For research on initial substance use, the most commonly used outcome variable is the "ever used" criterion. This criterion variable is a dichotomous outcome variable with two potential values: (a) use of the substance at least once in one's lifetime or (b) never having used the substance in one's lifetime. This type of variable has been referred to as a one way transition variable or a nonrepeatable event because once adolescents have used a substance they cannot return at a later point in time to the "never used" category. This is the type of data that is used for testing stage-like phenomenon.

Another characteristic of the data used in research on initial substance use is that there are two types of predictor variables: (a) stable predictor variables where a subject's status remains constant and (b) unstable one-way transition variables that continue to change over the course of the longitudinal study (Dwyer & Feinleib, 1992, p. 6-7). For example, predictor variables such as childhood temperament, personality, and ethnicity remain stable in longitudinal studies of the predictors of adolescent marijuana use. That is, the status of the subject on these predictor variables does not change throughout the course of a longitudinal study. For these variables, the stage
transition is obvious (e.g., childhood problems always precede substance use). In these cases, traditional statistical methods using two-wave designs can be used to test whether the hypothesized predictor variable such as childhood temperament is predictive of substance use.

However, change in many other predictors of adolescent marijuana use may not precede change in adolescent marijuana use. For example, initial cigarette smoking is a predictor variable that can change over the course of a longitudinal study that is attempting to predict marijuana use. For some adolescents, change in smoking status may follow marijuana use. Many predictors of marijuana use are similar to cigarette smoking (e.g., alcohol use, the use of other drugs, engaging in other problem behaviors, deviant peer bonding, parent bonding, self-efficacy, psychopathology and substance related attitudes and beliefs; see Braucht, Brakarsch, Follingstad & Berry, 1973; Sadava, 1987).

For unstable predictor variables, two-wave analyses cannot identify which variable truly precedes another (Dwyer & Feinleib, 1992, p. 6-7). In this article, we show how log-linear models can test hypotheses regarding which variable is likely to precede the other (e.g., the gateway hypothesis).

The Current Research

The purpose of the current study is to illustrate how log-linear models for square contingency tables can be used to test the major hypotheses regarding the relationship between cigarette and marijuana use. We chose this area of research to illustrate the use of log-linear models because attempts to explain the relationship between cigarette and marijuana use have stimulated considerable controversy (e.g., Baumrind, 1983; Hays et al., 1987; Huba, & Bentler, 1982; Martin 1982; O’Donnel & Clayton, 1982) and previous research has not identified a statistical approach that can test the major theoretical hypotheses.

An Illustrative Analysis

Illustrative Data

Our illustration requires a longitudinal study with at least three waves of assessment because the log-linear models that we illustrate would be underidentified if fewer waves were chosen (Bishop, Fienberg & Holland, 1975). Unfortunately, multiwave data in substance use research is rare. In addition, most multiwave studies in this area of research have extremely
high subject attrition rates (e.g., Kaplan, Martin & Robbins, 1984; Newcomb & Bentler, 1986).

The data for this study were collected as part of the Television, School and Family Project (TVSFP; Flay et al., 1988). This study was chosen because the data set included four waves of data. Although the study intervention influenced many mediating variables, the intervention did not influence cigarette or marijuana use (Flay et al., 1995). Thus, rates of cigarette and marijuana use were similar across all conditions. A total of 2,658 students completed questionnaires at all four waves. Similar to other studies in this area of research, the subject attrition rate was high. Only 36.2% of the students completed questionnaires at all four waves. Thus, our data only approximates the relationship between cigarette and marijuana use and we only use this data to illustrate the use of log-linear models. The high attrition rates preclude any substantive inferences that can be drawn from this data.

The initial sample consisted of 7,351 seventh grade students in 169 classrooms in Los Angeles County (representing 35 public schools in four school districts) and 67 classrooms in San Diego County (representing 12 public schools in two school districts). Students in the initial sample later completed follow-up questionnaires at four months, 18 months (eighth grade) and 28 months (ninth grade). The pretested students were 49.3% male and 50.7% female. They were 35.1% Hispanic, 31.8% White, 16.7% Black, and 16.4% other (primarily Asian). Most of the students (94.6%; N = 6,956) responded to the drug use questions at the pretest. The final student sample with complete data at all four waves was 35.4% Hispanic, 35.1% White, 10.6% Black, 18.9% other (primarily Asian) and 47.6% were male. These percentages were similar to the initial sample with the exception that Blacks and males were slightly less likely to be included in the final sample.

Trained data collectors provided instructions and administered the questionnaires to entire classrooms. Expired air samples were collected under bogus pipeline conditions to increase the validity of self-reports of cigarette use. Cigarette and marijuana use were assessed on nine point scales that ranged from “never used in lifetime” to “daily use.”

Statistical Approach

Terminology

Table 1 illustrates the data used for a longitudinal log-linear model of a square contingency table and represents a cross-classification of data from a
four wave longitudinal study. The variables represented in the table are five point scales that indicate when subjects first used cigarettes and marijuana. The variable on the vertical axis indicates the first wave of assessment that the adolescent reported using cigarettes. The variable on the horizontal axis indicates the first time an adolescent used marijuana.

Each box in Table 1 is referred to as a “cell.” Each cell indicates the number of observations described by a particular temporal pattern of cigarette and marijuana use. For example, the cell labeled “H” describes subjects who never used either cigarettes or marijuana.

The diagonal of cells labeled with either a “P” or an “H” is referred to as the main diagonal. At the end of each column and row, Table 1 indicates the

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Note. Each variable indicates the first wave that the subject used the substance.
marginal frequencies that represent the total number of observations in each row or column.

Log-linear Models

The general approach for using log-linear models has been described in many standard textbooks (e.g., Agresti, 1984; Bishop, Fienberg & Holland, 1975; Haberman, 1974). This approach usually involves deleting some cells from the model and testing for quasi-independence among the remaining cells of the contingency table. However, the more recently developed approach used in this article has been referred to as an analysis of nonstandard log-linear models (Rindskopf, 1990). This approach relies upon a model matrix that is sometimes referred to as a design matrix. This model matrix is part of the general linear model and can be represented as

\[ Y = XB \]

where \( Y(N \times 1) \) is a vector of the natural logarithm of the predicted cell frequencies, \( N \) is the total number of cells, \( X \) is an \( N \times p \) model matrix where the columns represent the effects in the model and \( B \) is a \( p \times 1 \) vector of parameters where element \( i \) in \( B \) corresponds to column \( i \) in the model matrix and \( i \) indicates an effect.

The goodness-of-fit of log-linear models can be evaluated by a likelihood-ratio (LR) goodness-of-fit statistic. The parameters in a model are only interpretable when the overall LR indicates that the model fits the data. More parameters can be added to a model to improve the goodness-of-fit of the model. Using the LR goodness-of-fit test for nested models, the researcher can attempt to identify the most parsimonious log-linear model with the fewest parameters that fits the data. The LR test is usually preferred over the Pearson goodness-of-fit test because the LR test can be used in comparing the fit of nested models. A pair of models is said to be nested when one model consists of a subset of the parameters used in the other model.

In addition to examining the LR tests, it is important to examine the parameters in the model (e.g., negative and positive parameter values inform about the direction of the effects). The size of a parameter estimate also indicates the relative importance of the parameter to the overall model (see Alba, 1988).

The nonstandard log-linear models for our analyses were specified using PROC CATMOD in SAS (1988). For SAS manuals, the model matrix is referred to as a response matrix.
Statistical Models

A great number of nonstandard log-linear models can be specified. To avoid experiment-wise error and specification searches that can capitalize on idiosyncrasies in the data, a strong theoretical justification must be made for testing a model. We provide a theoretical justification for all of the log-linear models we test.

A Test for the Presence of a Stage-like Progression

Previous researchers have suggested that more subjects try cigarettes before marijuana than try marijuana before cigarettes. This hypothesis can be tested with a two group chi-squared test. Subjects above the main diagonal in Table 1 tried cigarettes before marijuana. Subjects below the diagonal tried marijuana before cigarettes. Subjects on the main diagonal tried both cigarettes and marijuana at the same wave testing. Therefore, order of use cannot be determined for subjects on the main diagonal. There are also cells in which subjects tried only one substance. If a stage-like phenomenon is present, there should be more subjects who only use cigarettes than only use marijuana. That is, the cigarette only cells above the diagonal are consistent with a stage-like phenomenon. The marijuana only cells that are not consistent with a stage-like phenomenon are located below the diagonal. Therefore, the presence of the stage-like phenomenon can be tested by comparing the above diagonal group to the below diagonal group. An ordinary two group chi-squared test can be used to test the hypothesis that there are equal numbers of subjects in the above diagonal and below diagonal groups. The stage-like progression is present when the chi-squared test is rejected and there are more observations in the above diagonal group indicating that significantly more subjects are present in the cells consistent with the stage-like progression than there are in the below diagonal cells that are inconsistent with the stage-like progression.

The Statistical Independence Hypothesis

The statistical independence hypothesis argues that statistically independent processes insure that more adolescents experiment with cigarettes before marijuana. For example, some researchers have argued that cigarette use occurs at earlier ages than marijuana use so that it appears that cigarette use leads to marijuana use.

The marginal frequencies in Table 1 indicate the rates of initiation of cigarette and marijuana use at each wave of the study. These rates of use can
be examined to determine whether cigarette use occurs at earlier times than marijuana use.

The statistical independence of cigarette and marijuana use can be tested by the ordinary LR test of association. We refer to this test as the independence (I) model test. The LR test can be specified within the model matrix approach. Table 2 illustrates the model matrix used to test the independence, problem behavior and gateway models. Each row of the model matrix represents a cell in Table 1. The last two columns in Table 2 indicate which cell in Table 1 is represented by a row in Table 2. The variables in Table 1 have numerical designations that are given in parentheses below each wave of measurement. These numerical designations are used for specifying the design matrix (1 = initiating the substance before the beginning of the study (wave I), 2 = initiating between the first and second waves (wave II), 3 = initiating between the second and third waves (wave III), 4 = initiating between the third and fourth waves (wave IV) and 5 = never initiating). For example, the number “1” indicates that the substance was used before wave I and the H cell has a designation of 5,5.

The first column in Table 2 represents the constant term. The next four columns specify the main effects of marijuana use. For example, column 2 designates subjects who used marijuana at the first wave of testing. Columns 6 through 9 represent the main effects for cigarette use. These main effects represent the effects of the marginals that appear as row and column totals in Table 1. The model matrix is specified using dummy coding. Columns 10 through 12 in Table 2 are not used when testing the statistical independence hypothesis.

*The Healthy Group Hypothesis*

Problem behavior theory (Jessor & Jessor, 1977) argues that there is a "healthy group" of adolescents who do not use cigarettes and marijuana. The cell labeled H for "healthy group" in Table 1 includes subjects who never used cigarettes or marijuana. The healthy group hypothesis suggests that we would expect to observe more adolescents than expected under the I model in the H cell.

An H model can be specified by adding a parameter to the I model. For this nonstandard log-linear model, the tenth column of Table 2 is added to the model matrix. The tenth parameter designates the H cell. For columns one through nine in Table 2, dummy coding was used. For the tenth parameter, effects coding was used. The cell corresponding to subjects who never used either cigarettes or marijuana is given a value of -1 and all other cells have a value of 1. Similar to effects coding in ANOVA, the coefficient
### Table 2

**Model Matrix for the TVSFP Study**

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<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>1</td>
<td></td>
<td>5</td>
</tr>
</tbody>
</table>

Note. For the numbers under the columns labeled "cell indices, 1 = initiating the substance before the beginning of the study, 2 = initiating between the first and second waves, 3 = initiating between the second and third waves, 4 = initiating between the third and fourth waves and 5 = never initiating.
of the resulting terms can be interpreted as deviations from the average across cells (see Alba, 1988). Specifying such a parameter in the model matrix may improve the fit of the model if some of the discrepancy between the observed and expected frequencies in the I model occurs in the H cell.

The Problem Behavior Hypothesis

The problem behavior hypothesis would be supported if significantly more adolescents than expected under the H model begin using both substances at the same time. Except for the cell labeled H, all the cells on the main diagonal in Table 1 are marked with Ps. These cells correspond to adolescents who began using both cigarettes and marijuana within the same wave of testing. We would expect more subjects in these cells if the problem behavior hypothesis is correct. The numbers in column 11 which correspond to the P cells are coded as -1s and other cells are coded as 1s.

The Gateway Model

The gateway hypothesis argues that the use of a lower order substance increases the probability that adolescents will use higher order substances. The G cells in Table 1 represent cells where an adolescent used cigarettes before marijuana. There should be more subjects present in these cells if the use of cigarettes increases the probability that an adolescent will use marijuana. The additional parameter for the G model is specified in the twelfth column of Table 2. The G cells are coded as -1s and other cells are coded as 1s.

Reporting Inconsistencies

We defined students as responding inconsistently when they said that they had used a substance at one wave and had never used the same substance at a later wave. In order to determine the influence of inconsistent responders on our results, we examined our results in two ways: (a) excluding inconsistent responders from the analysis and (b) including inconsistent subjects by coding them as using a substance at the first wave they reported using the substance.
Results

Support for the Presence of a Stage-like Progression

In support of the hypothesis that a stage-like progression is present in the data, the two group chi-squared test was highly significant ($\chi^2 = 233.2, 1 \text{ df}, p < .0001$). As hypothesized, more subjects used cigarettes before marijuana. For the groups above and below the diagonal, the expected cell frequencies were 763.5. There were 47 observations in the below diagonal group representing subjects who used marijuana before cigarettes and 1,480 subjects in the above diagonal group that represents subjects who used cigarettes before marijuana.

Rejection of Statistical Independence

We can formally test whether there is a statistical association between cigarette use and marijuana use by the I model. The I model would only fit the data if there were no association between the times of marijuana and cigarette experimentation. The LR statistic for the I model has a value of 772.6 with 16 degrees of freedom. The statistic is highly significant ($p < .0001$) suggesting that different rates of initial use do not entirely explain why more subjects use cigarettes before marijuana.

Examining Observed versus Expected Frequencies

Agresti (1984) has suggested that researchers should compare the observed frequencies to the expected frequencies in square contingency tables to determine the extent to which marginal heterogeneity can produce uneven cell counts. Marginal heterogeneity can produce uneven cell counts in square contingency tables that can appear as a stage-like progression. For example, if all subjects used cigarettes at wave I and all subjects began using marijuana at wave II, there would be a stage-like progression from cigarette use to marijuana use. However, the expected and observed frequencies could be equal and so the LR could be equal to zero. This example illustrates that a stage-like progression can exist without statistical association.

Several researchers have suggested that cigarette smoking occurs at earlier ages than marijuana use so it is plausible that some of the stage-like progression is produced by uneven marginals.
Expected frequencies from the I model are an indicator of the extent to which statistically independent processes account for the stage-like progression because the expected frequencies are based on the number of subjects who begin using a substance at each wave and do not take into account any statistical association in the data. Table 3 shows the contingency table data for the TVSFP study. Row a in Table 3 gives the observed frequencies and Row b shows the expected frequencies for the I model.

Table 3
Comparisons of the Expected Frequencies of Several Models of Cigarette and Marijuana Use

<table>
<thead>
<tr>
<th>Wave of First Cigarette Use</th>
<th>Wave of First Marijuana Use</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Before</td>
</tr>
<tr>
<td>Before</td>
<td>1/86</td>
</tr>
<tr>
<td>Before 1/86</td>
<td>193a</td>
</tr>
<tr>
<td>Before 4/86</td>
<td>81.2b</td>
</tr>
<tr>
<td>Before</td>
<td>186.0c</td>
</tr>
<tr>
<td>P</td>
<td>G</td>
</tr>
<tr>
<td>Before 4/86</td>
<td>8</td>
</tr>
<tr>
<td>Before 4/87</td>
<td>21.8</td>
</tr>
<tr>
<td>Before</td>
<td>4.8</td>
</tr>
<tr>
<td>P</td>
<td>G</td>
</tr>
<tr>
<td>Before 4/88</td>
<td>2</td>
</tr>
<tr>
<td>Before 4/88</td>
<td>21.2</td>
</tr>
<tr>
<td>Before</td>
<td>5.0</td>
</tr>
<tr>
<td>P</td>
<td>G</td>
</tr>
<tr>
<td>Before 4/88</td>
<td>3</td>
</tr>
<tr>
<td>Before 4/88</td>
<td>17.4</td>
</tr>
<tr>
<td>Before</td>
<td>4.6</td>
</tr>
<tr>
<td>P</td>
<td></td>
</tr>
<tr>
<td>Never</td>
<td>3</td>
</tr>
<tr>
<td>Used</td>
<td>67.4</td>
</tr>
<tr>
<td>Used</td>
<td>8.6</td>
</tr>
<tr>
<td>H</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>209</td>
</tr>
</tbody>
</table>

Note. The dates in the table are the dates associated with each wave of measurement. Substance use was assessed at four waves of measurement.

a Observed frequencies. b Expected frequencies for I (independence) model. c Expected frequencies for the nonstandard model.
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Summing the expected frequencies for all the G cells in row b of Table 3, we obtain a total expected frequency of 281.7. The expected frequencies in the cells below the diagonal where marijuana use precedes cigarette use are considerably less than the total in the G cells (total expected frequency = 96.2). The fact that the expected frequency rate is three times greater in the G cells indicates that statistically independent processes appear to account for some of the stage-like phenomenon. That is, cigarette use tends to occur at earlier waves than marijuana use and this produces some of the stage-like phenomenon.

However, there are 407 subjects in the G cells so there are 125.3 more observations than the expected frequency of 281.7. This discrepancy between the observed and expected frequencies in the G cells suggests that there is a statistical association between cigarette and marijuana use that exaggerates the stage-like progression. These results suggest that more subjects use cigarettes before marijuana because (a) cigarette use begins at earlier waves of testing and (b) there is an as yet unidentified statistical association between cigarette and marijuana use.

Comparisons between observed and expected frequencies also can be used to determine whether a statistical association is in the hypothesized direction. For example, the healthy group hypothesis suggests that the H cell will have more subjects than expected. In support of this hypothesis, there are 217.8 more subjects than expected in the H cell in Table 3 (832 observed - 614.2 expected = 217.8).

In support of the problem behavior hypothesis, there were substantially more subjects in the P cells than expected (299 observed - 132.3 expected = 166.7).

As mentioned previously, there are 125.3 more observations than expected in the G cells. These results support the gateway hypothesis in suggesting that there are significantly more subjects who use cigarettes and then move on to future marijuana use.

**Nonstandard Log-linear Model Tests**

The full design matrix in Table 2 tests whether all of the statistical association in Table 3 can be accounted for by the three additional theoretically prescribed parameters that test the healthy group, problem behavior and gateway hypotheses. The results of this analysis are presented in Table 4. Table 4 shows that each of the individual parameter values relative to their standard errors are statistically significant. These findings lend support to the healthy group, problem behavior and gateway hypotheses.
Table 4
Maximum Likelihood Analysis of Variance Table for a Nonstandard Model With and Without Inconsistent Responders

Inconsistent responders included \((N = 2,658)\)

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Parameter Estimate</th>
<th>(df)</th>
<th>LR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cigarettes</td>
<td></td>
<td>4</td>
<td>472.21**</td>
</tr>
<tr>
<td>Marijuana</td>
<td></td>
<td>4</td>
<td>339.35**</td>
</tr>
<tr>
<td>Healthy Group</td>
<td>-.491</td>
<td>1</td>
<td>10.55*</td>
</tr>
<tr>
<td>Problem Behavior</td>
<td>-1.254</td>
<td>1</td>
<td>124.34**</td>
</tr>
<tr>
<td>Gateway</td>
<td>-1.163</td>
<td>1</td>
<td>89.27**</td>
</tr>
<tr>
<td>LR</td>
<td></td>
<td>13</td>
<td>29.41*</td>
</tr>
</tbody>
</table>

Inconsistent responders not included \((N = 2,180)\)

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Parameter Estimate</th>
<th>(df)</th>
<th>LR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cigarettes</td>
<td></td>
<td>4</td>
<td>363.55**</td>
</tr>
<tr>
<td>Marijuana</td>
<td></td>
<td>4</td>
<td>227.38**</td>
</tr>
<tr>
<td>Healthy Group</td>
<td>-.353</td>
<td>1</td>
<td>2.81</td>
</tr>
<tr>
<td>Problem Behavior</td>
<td>-1.526</td>
<td>1</td>
<td>78.53**</td>
</tr>
<tr>
<td>Gateway</td>
<td>-1.512</td>
<td>1</td>
<td>69.12**</td>
</tr>
<tr>
<td>LR</td>
<td></td>
<td>13</td>
<td>46.18**</td>
</tr>
</tbody>
</table>

Note. * = \(p < .01\). ** = \(p < .0001\).

The LR at the bottom of the table is an indicator of the overall fit of the model. A nested model test indicates that this model represents a substantial improvement in fit over the I model \((LR = 743.2, df = 3, p < .0001)\). The overall LR goodness-of-fit test of the final model \((LR = 29.41, df = 13, p < .01)\) is reasonably small given the large sample size. This finding suggests that the three parameter model fits the data. In further support of the goodness-of-fit of this model, Row c in Table 3 shows that there are no major discrepancies between the observed and expected frequencies for the three parameter model.

Parameter estimates are also presented in Table 4. The healthy group hypothesis parameter is statistically significant but small. The problem
behavior and gateway parameters are associated with larger effects. It should be noted that when testing more than one model the direction of signs can change so it is important to keep track of both the magnitude and sign of all parameter estimates when testing a series of models.

*The Effects of Inconsistent Responders*

For cigarette use, 8.4% of the subjects responded inconsistently and 4.2% had inconsistent responses for marijuana use. Thus, inconsistent responding was much less of a problem than subject attrition.

For the model with all subjects and for the model based on the subsample of subjects who responded consistently, the *LR* tests for the individual parameters are significant except for the healthy group model in the sample of subjects without inconsistencies. The effect of the healthy group is small relative to the other parameters in the model that included inconsistent responders so the difference may in part be due to the smaller sample size used in the consistent responders analysis. However, this finding also suggests that support for the healthy group model may depend upon inconsistent responders.

*Alternative Analyses*

In other areas of research, other types of models may be useful for testing stage-like phenomena. In this section, we illustrate other types of models that may be useful in other applications.

*Logistic Regression*

It is also worthwhile to compare our approach with the traditional two-wave logistic regression analyses that have been widely used in previous substance use research. This approach involves determining whether cigarette use at wave I predicts marijuana use at wave IV among those subjects who were not using marijuana at wave I. Cigarette use does predict marijuana use (Odds ratio = 3.6, *p* < .0001) and marijuana use at wave I also predicts cigarette use at wave IV (Odds ratio = 4.9, *p* < .05) among those subjects who were not using cigarettes at wave I. Thus, the results of traditional logistic regression analyses yield the same confusing pattern of bidirectional results reported in the previous literature (see Newcomb & Bentler, 1986).
Marginal Homogeneity

Another test of interest is the test of marginal homogeneity. The statistical independence hypothesis as described in the current article has two parts: (a) the classifications are independent — I model and (b) the marginal distribution of marijuana use onset is shifted relative to the cigarette use distribution such that cigarette use occurs before marijuana use. The test of the equality of the marijuana and cigarette distributions is referred to as a test for marginal homogeneity. Marginal homogeneity is rejected when the two marginal probabilities are not equal to the corresponding column marginal probabilities. That is,

$$H_0: p_{ij} = p_{i.} \text{ (for } i = 1, 2, \ldots, r)$$

For an $r \times r$ table, where $i$ equals the number of columns or rows in the square contingency table, $p_{ij}$ denotes the marginal row proportions and $p_{.,i}$ denotes column proportions that are obtained by summing the joint proportions from the square contingency table. The test statistic is

$$\chi^2 = d'V^{-1}d$$

where $d$ is a column vector of any $(r - 1)$ differences in which $d_i = n_{i.} - n_{.,i}$ and $V$ is an $(r - 1) \times (r - 1)$ covariance matrix of the $d_i$'s (Everitt, 1977) and $n_{i.}$ and $n_{.,i}$ equal the number of subjects in each row and column, respectively.

Inspecting Table 3, we can see that the row and column marginals are clearly not equal. Therefore, the marginal homogeneity hypothesis is strongly rejected ($\chi^2 = 1,207.8$, $df = 4$, $p < .0001$). The marginal frequencies for cigarette use show that many subjects had experimented with cigarettes before the study began ($N = 1,033$, 38.9%). In contrast, few subjects had used marijuana before the study began ($N = 209$, 11.0%). At the second and third waves of testing, more subjects began using cigarettes than began using marijuana (see Table 3). At the last wave, only 221 adolescents began using cigarettes and 236 began using marijuana (see marginal frequencies of Table 3). These results are consistent with previous research that suggests subjects use cigarettes at earlier ages than marijuana.

Marginal homogeneity can also be evaluated by nonstandard log-linear models. The cigarette and marijuana parameter estimates for each row and column in Table 3 are not presented in Table 4 because these eight parameters do not test important hypotheses for the current application. As
indicated by our marginal homogeneity test, these parameters are highly significant because marginal totals vary greatly (see Table 3).

Quasi-independence Models

In addition to using the model matrix approach, our theoretical models can be tested with traditional quasi-independence models. Quasi-independence can be particularly useful for subgroup analyses. For example, a researcher may be interested in testing whether the time till use of marijuana is independent of when cigarettes were first tried among the subgroup of subjects who used cigarettes before or at the same time as when they used marijuana. This model involves a subgroup analysis of those subjects in the table who are on the main diagonal or above it. Quasi-independence fits for this group ($\chi^2 = 8.20, 6 \text{ df}, p > .05$) and for the subgroup of subjects below the diagonal ($\chi^2 = 2.33, 3 \text{ df}, p > .05$) who used marijuana first. Similarly, there is no association ($\chi^2 = 6.02, 3 \text{ df}, p > .05$) for the subgroup of subjects above the diagonal who tried cigarettes first. This model suggests that for those adolescents who used cigarettes before marijuana, time till use of marijuana is independent of when cigarettes were used.

Quasi-independence models can also be used to test the problem behavior and gateway hypotheses. For example, a quasi-independence problem behavior model can be tested where the cells on the main diagonal have been deleted. The problem behavior model is

\[
\ln m_{ij} = u + \beta_i + \alpha_j + (\alpha\beta)_{11} + (\alpha\beta)_{22} + (\alpha\beta)_{33} + (\alpha\beta)_{44}
\]

where $m$ represents the expected value of the cell count, $u$ is the constant term, $i$ represents the row value for hard drug use, $j$ represents the column value for marijuana use, $\alpha$ represents the row parameter and $\beta$ represents the column parameter. In support of the problem behavior hypothesis and similar to the findings for the nonstandard log-linear model, the LR test for this model represents a substantial improvement in fit over the I model ($LR = 91.2, df = 11, p < .0001$).

For the model matrix approach, we treated all the P cells as a single parameter which implies that the increments are the same in every cell. This assumption may be incorrect and the model could fail to fit the data for this reason. The problem behavior hypothesis can be tested with multiple parameters to fit the excess number of observations in each diagonal cell where each parameter represents a single main diagonal cell. This multiple
parameter model, that does not include H and G parameters, is identical to the quasi-independence model tested previously and has exactly the same overall goodness-of-fit. Thus, the P model does not fail to fit the data due to heterogeneity of cell increments. In addition, this shows that the quasi-independence approach treats each cell as a separate parameter. This characteristic of nonstandard log-linear models may be undesirable or desirable depending upon the researcher’s hypothesis. The model matrix approach has greater flexibility because it can treat a cell as a single parameter or treat groups of cells as a single parameter.

Another equivalent method that has been widely used for estimating the LR for a nonstandard H model with no G or P parameter is to simply re-estimate the I model with the H cell deleted from the contingency table which yields equivalent results for a model matrix with an H parameter.

The gateway quasi-independence model is

\[
\ln m_j = u + \beta_i + \alpha_j + (\alpha \beta)_{11} + (\alpha \beta)_{22} + (\alpha \beta)_{33} + (\alpha \beta)_{44} + (\alpha \beta)_{21} + (\alpha \beta)_{31} + (\alpha \beta)_{32}.
\]

The quasi-independence gateway model fits the data (LR = 8.1, df = 5, \(p > .05\)) and by a nested model test (LR = 83.1, df = 6, \(p > .0001\)) offers a significant improvement in fit over a quasi-independence main diagonal model. Thus, our results are similar for quasi-independence and nonstandard models.

**Examining Standardized Differences**

The method of comparing observed and expected frequencies in this article is recommended by Agresti (1984) as a method of identifying how marginal distributions influence expected cell frequencies. This approach should not be confused with similar approaches that attempt to identify which cells make the largest contributions to the overall magnitude of the \(LR\) test. For example, standardized residuals as opposed to raw differences between expected and observed observations are useful because the size of the residual does not depend upon the number of subjects in the cell. Thus, standardized residuals allow for meaningful comparisons between observed and expected frequencies across cells to determine which cells can be parameterized to improve model fit. For example, one of the largest residuals for the I model was the H cell (-2.00).

In other applications that involve testing different theories, other types of log-linear models may be tested. The model matrix approach allows the
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specification of many different types of models (Rindskopf, 1990) and
previous researchers have described many potentially interesting quasi-
independence models. For example, Goodman (1978) has formulated
several methods for testing whether similar patterns of expected cell
frequencies occur above and below the main diagonal. He refers to these
models as diagonal-parameter models. We recommend that readers
interested in applying log-linear models to new areas of research consult this
extensive literature (e.g., Agresti, 1984; Bishop, Fienberg & Holland, 1975;

Discussion

The purpose of the current article was to illustrate how log-linear models
for square contingency tables can be used to test stage theories in
psychological research. In order to illustrate that this approach can test
theoretically interesting hypotheses, we employed an illustrative example
from research on adolescent substance use. Previous substance use research
and the current research has shown bidirectional relationships in which
marijuana use predicts cigarette use and cigarette use predicts marijuana use
(Newcomb & Bentler, 1986). It is unclear how these results relate to the
major theoretical explanations for the stage-like progression from cigarette
use to marijuana use.

A great deal of controversy and speculation has centered around
explanations for the stage-like pattern of initial substance use (Baumrind,
1983; Hays et al., 1987; Huba & Bentler, 1982; Martin, 1982; O’Donnel &
Clayton, 1982). We showed how nonstandard log-linear models can test
several theoretically plausible explanations for the stage-like phenomenon
between cigarette and marijuana use. Our illustration may help clarify some
theoretical and statistical issues in this area of research and illustrates how
nonstandard log-linear models may be used to address some of the important
theoretical questions. However, the substantial subject attrition problem in
the TVSFP study (Flay et al., 1995) did not allow accurate testing of these
hypotheses. The subject attrition problem in the TVSFP study is typical of
other multiwave longitudinal studies in this area of research (Kaplan, Martin
& Robbins, 1984; Newcomb & Bentler, 1986). The current research
suggests the need for new multi-wave studies with lower subject attrition
rates.

In addition, the current research suggests that many subjects respond
inconsistently when they are asked whether or not they have previously used
cigarettes or marijuana. These results suggest that future researchers
examining the stage-like phenomena should investigate the source of these
inconsistencies in greater detail because simply identifying and eliminating inconsistent responses creates a problem. A researcher can only identify inconsistent responders who first report using a substance and then not using a substance. This research cannot identify inconsistencies from subjects who underreport their substance use at an earlier wave and then respond accurately at later waves. Thus, future research requires more sensitive methods of detecting the reasons for these reporting inconsistencies.

One potentially important aspect of assessing the extent to which cigarette use is a risk factor for marijuana use may be to establish that the probability of trying marijuana conditional upon having tried cigarettes is higher than the probability of trying marijuana conditional on not having tried cigarettes. This issue can be addressed to a certain extent by traditional statistical methods and structural analysis (Newcomb & Bentler, 1986). For example, our logistic regression analyses show that subjects who use one substance are at higher risk for using other substances. However, our results illustrate some important limitations to examining pairs of conditional relationships. Prior researchers have suggested comparing the magnitude of the conditional probabilities (e.g., the probability of marijuana use based on prior cigarette minus the probability of cigarette use based on prior marijuana use) to determine which variables temporally precedes another. This approach is a fallacy similar to the old cross-lagged design approach of determining temporal precedence by subtracting predictive correlations (see Rogosa, 1988). It has been suggested that more useful approaches to understanding temporal relationships between variables is to develop new approaches that utilize multi-wave data (Collins & Horn, 1991; Dwyer & Feinleib, 1992). For example, our log-linear model approach clearly shows that statistical association between cigarette and marijuana use produces more subjects who make the transition from cigarettes to marijuana. This type of hypothesis cannot be tested by examining patterns of conditional probabilities in two-wave analyses.

Similarly, the problem behavior hypothesis, which is a test that change in both variables occurs at the same time, cannot be tested with two-wave data. Our study shows that subjects were likely to adopt the use of both cigarettes and marijuana within the same wave of testing. This is a theoretically important issue in substance use research (Jessor & Jessor, 1977) and may also be an important test in other areas of research.
The Problem of the Unknown Third Variable

The unknown third variable problem is an issue for all longitudinal non-experimental research and should be given adequate consideration when interpreting the results of log-linear models. For example, our results could be produced by an averaging artifact among heterogeneous respondents. That is, two different populations of respondents may have been exposed to both cigarettes and marijuana. The different cohorts may have been exposed at different times. Under these circumstances, a spurious association can be created. This problem in the analysis of contingency tables has been referred to as Simpson's paradox (Simpson, 1951).

Simpson's paradox illustrates the importance of understanding factors that produce marginal distributions. Another way that marginal distributions could have influenced our results is that the first attempt at smoking may occur before marijuana use because cigarettes are more widely available at earlier ages than marijuana (Baumrind, 1985, Cohen, 1972). That is, the greater availability of substances such as cigarettes increases opportunities to use cigarettes at younger ages. As a consequence, adolescents are more likely to have an opportunity to use cigarettes before they have an opportunity to experiment with marijuana. The contingency tables illustrated in this article describe different rates of onset of cigarette and marijuana use but they do not explain why these marginal rates exist. In order to fully understanding the statistical association between cigarette and marijuana use, future research is required to identify the determinants of different rates of onset (e.g., supply and demand factors).

In addition, unknown third variables can influence the results of the main diagonal hypothesis — problem behavior test. One potential explanation for a positive main diagonal test is that there may be something about the natural history of substance use that causes adolescents to be exposed to and adopt different substances at the same time. To address this question, future studies are required to determine the circumstances under which adolescents adopt cigarettes and marijuana.

The Problem with Length of Follow-up

As is the case in all longitudinal studies, the length of time between waves of testing may influence the results of a test. If there are short temporal sequences between cigarette and marijuana use, longitudinal
studies with shorter time intervals between assessment periods will identify these sequences and there will be fewer subjects on the main diagonal. However, these short temporal sequences may not be detected when longer time intervals between assessment periods are used. In these cases, most subjects may appear on the main diagonal. For example, clustering along the main diagonal would occur in our study with year long time intervals if the time between the adoption of cigarette use and marijuana use is only a few months. Thus, an alternative explanation for a statistically significant main diagonal test in our study is that shorter stage-like sequences between marijuana and cigarette use may exist that were not detected by our annual follow-up data.

This issue suggests the need for research on the mean and standard deviation of the time between temporal sequences. This research can be used to determine the optimal length of time between assessment periods.

*Limitations Associated with Log-linear Models*

Using nonstandard log-linear models for the analysis of multi-wave data has the standard limitations associated with the use of any log-linear approach. As mentioned previously, the approach dealt with in the current article can only be used to test hypotheses regarding dichotomous non-repeatable events. Furthermore, lack of statistical control can be problematic because the approach we have illustrated only involves two variables. Although log-linear models can be developed that include more variables, the inclusion of more variables can rapidly lead to sparse contingency tables where the magnitude of the $LR$ may not possess the desired null distributions and existence problems may occur for parameter estimates. In cases where the researcher expects that these problems may be present, Goodman (1978) suggests comparing the Pearson and $LR$ ratio statistics. When both of these statistics are comparable than the researcher can be reasonably certain that the sample size is adequate.

A potential multivariate analogue to the log-linear models presented in this article are generalized estimating equations (GEE; Zeger, Liang & Albert, 1988). Within the GEE framework the problem can be formulated to represent a repeated measures logistic regression. The procedure allows for both static and time-varying covariates to be specified as lagged or synchronous predictors. For example, using these models marijuana use could represent the outcome variable and the five-point cigarette scale could be dummy coded as a predictor variable. Testing for interactions between the cigarette variable and time would represent a test of the problem
behavior hypothesis and the dummy coded predictor variable would be a test of the stage hypothesis.

Latent growth modeling (LGM; Collins & Wugalter, 1992) allows for the investigation of the development of substance use, where the initial status, developmental trajectories and predictors of use can be examined at both the inter and intra-individual level.

These techniques (GEE & LGM) allow for an assessment of the relative importance of psychosocial risk factors for adolescent substance use development (Petraitis, Flay & Miller, 1995) in conjunction with the effects of the initiation and level of use of other substances. In addition, both GEE and LGM methods allow for the handling of various types of missingness, including missingness due to attrition, a major concern with most longitudinal studies of substance use.

Directions for Future Research

Previous research has focused on whether initiation of one substance is predictive of initiation of another. Future research also must begin to examine whether level of use of a substance predicts initiation and level of other substances. Several alternative explanations exist for why one drug is initiated before another. For example, those who use cigarettes may be more prone to using amphetamines because the stimulant properties of cigarettes no longer provide a sufficient desired effect (Horger, Giles & Schenk, 1992). Alternatively, progression may ensure increased opportunities for use or greater exposure to other illicit substances.

References


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