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An Investigation into Selected Antecedents of Behavior Modification*

Youjae Yi
Seoul National University

How can one modify one's behavior? If so, how can one maintain the modified behavior? These are questions relevant to every aspect of our life. There have been many studies that try to explain one's behavior, but relatively few studies on changing and maintaining the changed behavior. As behavior becomes habitual or addictive, it will be more difficult to modify. Even though one may succeed in modifying behavior temporarily, maintaining the modified behavior will be difficult. Such behavior runs a wide gamut from addictive behaviors like alcoholism, smoking, drug abuse to a minor habit like trembling legs while talking. Though they differ in their scope and nature, there are common characteristics. One's intention might be in one direction, while attitude or habits are in the opposite direction. Then there will be a conflict between intention and habit. Thus one's attitudes or intentions are not enough to explain one's behavior. Then what are the factors that are associated with maintaining the modified behavior? This study tries to address this question in the context of quitting smoking.

Cigarette smoking has been judged to be a dangerous habit. It can lead to a variety of ailments and serious disorders, from impaired breathing to heart disease (Krasnegor 1979). Many people are attempting to quit smoking, and many treatment programs are prevalent. Many treatment programs claim 70 to 80 percent success in quitting. Their statistics are somewhat misleading since they are based on the short term results, usually within 3 months. Among the short-term quitters, many relapse into smoking in 6 months or 1

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year. Thus the important issue is how to maintain abstinence rather than how to quit for a short period.

This study examines the short-term quitters one year after quitting. Their long-term quitting behaviors may be maintaining abstinence or relapse into smoking. One's behavior can be better understood and explained in the context of personal factors, whether subjective or objective. Though the subjective factors such as attitudes are useful in explaining the behavior, they are frequently difficult to conceptualize and measure. Obtaining high reliability and validity of such measures are a burdensome task to the researchers. On the other hand, objective factors are easier to measure and more accessible. Employment status is one of such objective factors. In modern society, job is not a means of life anymore, but it has become a part of life. Considering that people spend more than a third of their time on work, this can be easily understood.

One also does not live in a vacuum, but in a society. People are born in a family, and grow up to become members of certain groups. So one is implicitly and explicitly under the influence of others such as reference groups. Thus there is a need for incorporating the relevant other's behavior. In the context of quitting smoking, the smoking status or smoking history of the parents seems to be relevant. The study examines the interrelationships among these factors, i.e. one's quitting behavior in the long run, employment status, and relevant other's smoking behavior. Some alternative models will be compared and assessed by the empirical data from Northern California Smoking Relapse Study (NCRCS).

The categorical nature of the variables can be noted. Unlike the quantitative variables, the qualitative variables pertain to classifications rather than to measurements. They include nominal variables such as employment status, for which the categories (unemployed, employed) are unordered. All the variables in this study are in the nominal scale, and the usual linear regression model is not suitable. Log-linear models are used in this study without designating dependent and independent variables. Then the logit model will be used by taking the dependent variable, here the long-term quitting behavior. The relationships between the two models will be discussed from theoretical and empirical viewpoints.

HYPOTHESES

There are many potential relationships among the variables, but some relationships are hypothesized a priori. The hypotheses and the rationales or relevant theories will be discussed.

The study is interested in the long-term behavior of ex-smokers by a follow-up one year after quitting. For the successful treatment on quitting, this long-term behavior will be more important than the short-term behavior right after the program. Once they quit smoking, there will be many factors which help or threaten people's maintaining the non-smoking status.

Employment Status

One's employment status is one of the important individual factors. Employed persons are more likely to maintain abstinence, compared with the unemployed persons. There are increasing numbers of non-smokers, and their pressure against smoking in their presence. Employed people spend much time with other people, and are likely to be under these implicit pressures. They also spend most time in the public places many of which do not allow smoking. This will help them to resist the urge to smoke as overt and covert constraints. On the other hand, unemployed people will have more private time at private places. So there will be fewer constraints such as non-smoking regulations. Also the pressure from non-smokers will be less since they don't have to stay with others at a workplace.

From the psychological viewpoint, smoking can be construed as an activity. Employed people participate in many activities, and will have less need for another activity, e.g. smoking. Unemployed people will have fewer activities, and psychologically need more activities. Another relevant theory on smoking is that smoking is related to the stress. Stress is, however, likely to differ between workers and non-workers in nature and amount. On one hand, workers are likely to have more stress due to the job. They will feel more tired physically also. On the other hand, non-workers are likely to be less under the job strain. Therefore they feel less stress. This reasoning will predict that is related to unemployment the lower smoking for the unemployed. But this will not always be the case. For the unemployed, they might have less chances for so-called self-actualization. In that sense, the unemployed might have more psychological stress as a result of fewer channels for

achievement. Thus, it is likely that there is an association between one's employment status and maintaining abstinence.

H1: There is an association between one's employment status and long-term quitting behavior.

Reference Group

One's behavior or habit seems to be influenced by reference groups such as peers, parents, or media stereotypes (e.g. models in cigarette ads). Smoking seems to be initiated as a result of imitative or modelling process of relevant others. According to social learning theory, one forms attitudes or habits not only by direct experience but also through vicarious experience such as observation. Such observational learning processes seem to be important for smoking. Parents who smoke clearly influence the smoking behavior of their children. Borland and Rudolph (1975) found that parental smoking is the second best predictor of smoking behavior in high school students. So parent's smoking history is hypothesized to be associated with the quitting behavior of a person.

Social Comparison Theory

Social comparison theory by Festinger (1954) has two basic ideas: 1. People have a drive to evaluate themselves. 2. In the absence of objective nonsocial criteria, we evaluate ourselves by comparison with other people. Given a range of possible persons for comparison, someone who is similar and available to one is chosen. Then for female ex-smokers, mother seems to used as a comparison person. So it is hypothesized that mother's smoking history is associated with the quitting behavior of female ex-smoker.

H2: Mother's smoking history is associated with a female ex-smoker's long-term quitting behavior.

DATA

Subjects were recruited from a number of formal smoking-cessation programs in the San Francisco Bay and Sacramento Delta regions of California. The recruitment process consists of two steps. First, the partici-

pant programs were given "agreement to be contracted" forms, and interested candidates were free to mail their forms. After 3 months, each candidate was called to determine her current smoking status. Those stating they maintained abstinence were invited to join NCSRS. In order to corroborate the self-reported smoking status, saliva thiocyanate (SCN) was used. For the current study, all female ex-smokers were used, with a sample size of 180. A further detailed description can be found in Swan et al. (1985).

Measures

Abstinence and Relapse: Long-term quitting behavior is measured after one year with the variable ABSTIN. This is 0 for relapse, and 1 for abstinence. Abstinence is defined as no reported smoking and and SCN corroboration. Relapse is defined as reported smoking in any amount at anytime before the examination or a SCN value greater than or equal to 120 ug / ml. Compared with other studies solely based upon self-reports, this corroboration will provide more reliable data Employment Status: The employment status of the ex-smoker is indicated by the variable UNEMPLOY. This has two categories, i.e. employed and unemployed. This is 0 for the employed and 1 for the unemployed.

Mother's Smoking History: Each participant is asked to provide information on the smoking and / or quitting history of her mother. The forced-choice responses were grouped into three categories for analysis: "never tried to quit and / or tried to quit but couldn't, i.e. currently smoking," "smoked, but quit," and "never smoked." The first category indicates the currently smoking mother, while the other two categories indicate the currently nonsmoking mother. This is captured by the variable MOMHIST, which means the smoking history of one's mother. Two dummy variables can be used to represent the category. They are MOMNEVER and MOMSTOP. MOMNEVER is 1 if the mother never smoked, while MOMSTOP is 1 if the mother smoked, but has quitted. Respondents whose mothers are still smoking are represented by zero for both MOMNEVER and MOMSTOP. Table 1 provides the brief description of the variables to be used in the study.

〈Table 1〉 Description of Variables in the Analysis

Variable	Brief Description
ABSTIN	0=Relapse, 1=Abstinence
UNEMPLOY	0=Employed, 1=Unemployed
MOMHIST	Smoking History of the mother
	1=Smoked, not quit(Smoking)
	2=Smoked, but quit
	3=Never smoked
MOMSTOP	Dummy 1=Mom smoked, but quit
MOMNEVER	Dummy 1=Mom Never Smoked

* Dummy variables are 1 if the definition of the variable is satisfied

METHOD

The data can be cross-tabulated in a frequency table. There are three variables, i.e. employment status, long-term quitting behavior, and mother's smoking history. A 2×2×3 contingency table is made, and summarized in table 2.

〈Table 2〉 Observed Frequency Table

		EMPLOYED	UNEMPLOYED	TOTAL
RELAPSE	SMOKING	13	4	17
	QUIT	11	1	12
	NEVER SM	15	14	29
	TOTAL	39	19	58
PSTINENCE	SMOKING	23	4	27
	QUIT	22	2	24
	NEVER SM	59	12	71
	TOTAL	104	18	122

A model in the contingency table analysis is a statement of the expected cell frequencies of a cross-tabulation as functions of parameters representing various marginal categories. The parameters are related to odds and odds ratios. There are two major approaches to log-linear modelling of contingency table data (Knoke and Burke 1980). First, the general log-linear model does not distinguish between independent and dependent variables. All variables are treated alike as "response variables" whose mutual associations are explored. Second, in the logit model one variable is chosen as the dependent variable. The criterion to be analyzed is the expected odds as a function of the other independent variables. Bishop (1969) has, however, demonstrated that there is a close relationship between log-linear models and logit models. This relationship will be discussed later, mean while, the general log-linear models will be examined first.

Log-linear Models

It has been already mentioned that the data are frequencies or counts rather than continuous measurement. Log-linear models will be used to analyze these qualitative data. Log-linear models are quite general in at least two aspects (Goodman 1978). First, interaction effects are an integral part of the log-linear model. A "saturated" model includes all possible interactions. And the interactions can be tested for their significance in a systematic way. Quantitative models, on the other hand, are typically assumed to be linear with no interactions or linear with only a small number of interactions added. Interaction terms in quantitative models like linear regression models are sometime included as product of the explanatory variables. However, when interaction terms are included, the results are often difficult to interpret because they depend on whether the explanatory variables are standardized along with other related issues (Mosteller and Tukey 1977). Symmetric interactions in the log-linear system appear to have natural interpretation within the context of hierarchical system.

Second, normality is typically assumed in the analysis of a quantitative dependent variables using the usual regression methods. In practice the dependent variable may or may not be normally distributed around a regression

line. Log-linear modelling approach for qualitative data depends less upon such distributional assumption. Some basic models in the context of three-way table will be discussed below.

We begin discussion of models for a 2×2×3 contingency table by presenting one possible model. Let m_{ijk} be the number or frequency of cases in cell i,j,k which are expected to be present if the model is true.

$$m_{ijk} = \tau\tau_i^{u}\tau_j^{a}\tau_k^{m}\tau_{ij}^{ua}\tau_{ik}^{um}\tau_{jk}^{am}\tau_{ijk}^{uam} \quad (1)$$

If we take the logarithm of the equation (1), then we get the following equation (2).

$$\ln m_{ijk} = \lambda+\lambda_i^{u}+\lambda_j^{a}+\lambda_k^{m}+\lambda_{ij}^{ua}+\lambda_{ik}^{um}+\lambda_{jk}^{am}+\lambda_{ijk}^{uam} \quad (2)$$

This is the saturated model in that all possible effects are modeled by the parameters. So the first line of equation (2) indicates the main effects, and the second line shows the two-way or first-order interactions. The last line is the three-way or second-order interaction effect. There are some constraints needed for the models.

(1) Each sum of main effects should add up to zero.

$$\sum\lambda_i^{u} = \sum\lambda_j^{a} = \sum\lambda_k^{m} = 0$$

(2) Each sum of two-way interaction effects should add up to zero in each dimension.

$$\sum\lambda_{ij}^{ua} = \sum\lambda_{ij}^{ua} = 0$$
$$\sum\lambda_{jk}^{um} = \sum\lambda_{jk}^{um} = 0$$
$$\sum\lambda_{jk}^{am} = \sum\lambda_{jk}^{am} = 0$$

(3) Each sum of three-way interaction effects should add up to zero.

$$\sum\lambda_{ijk}^{uam} = \sum\lambda_{ijk}^{uam} = \sum\lambda_{ijk}^{uam} = 0$$

These constraints are necessary and sufficient for both unique solution for parameters and unique interpretation of structure of model (Knoke and Burke 1980). There are three variables:. employment status (UNEMPLOY or U), quitting status (ABSTIN or A), and mother's smoking history (MOMHIST or M). Using the convention, this model will be indicated by (UAM). A hierarchical model is defined as the model where the inclusion of a particular n-way interaction *requires the inclusion of all lower-order* interactions involving the same variables. So (UAM) indicates that the model has the terms UAM, UM, UA, AM, U,A, and M. Beside this saturated model where associations between pairs, of variables do vary with levels of the 3rd variable, there are several other models which are parsimonious.

For example, there is a complete independence model. Here the cell frequencies are hypothesized to be predicted by one-way marginals, and there are no associations assumed among the three variables. This can be represented in the log-linear model notation as follows:

$$\ln m_{ijk} = \lambda + \lambda_i^u + \lambda_j^a + \lambda_k^m$$

Logit Model

In the general log-linear model there is no dependent variable. The primary purpose is to understand the relationships among the factors. But we might be interested in explaining a variable, i.e. dependent variable. Here the long-term behavior of ex-smokers will be the variable to be explained. Then other variables like employment status and mother's smoking history will be used as dependent variables. We will show the algebraic equivalence that logit model can be derived from log-linear model. Consider the saturated model from our saturated model (UAM).

$$\ln m_{ijk} = \lambda + \lambda_i^u + \lambda_j^a + \lambda_k^m + \lambda_{ij}^{ua} + \lambda_{ik}^{um} + \lambda_{jk}^{am} + \lambda_{ijk}^{uam})$$

Given a particular combination on UNEMPLOY(i) and MOMHIST(k), the odds of having abstinence is

$$\frac{Pr(abstinence)}{Pr(relapse)} = \frac{m_{i2k}}{m_{i1k}}$$

The log-odds is then

$$\ln\frac{m_{i2k}}{m_{i1k}} = \ln m_{i2k} - \ln m_{i1k} = (\lambda - \lambda) + (\lambda_i^u - \lambda_i^u)$$
$$+ (\lambda_2^a - \lambda_1^a) + (\lambda_k^m - \lambda_k^m) + (\lambda_{i2}^{ua} - \lambda_{j1}^{ua}) + (\lambda_{2k}^{am} - \lambda_{1k}^{am})$$
$$+ (\lambda_{ik}^{um} - \lambda_{jk}^{um}) + (\lambda_{i2k}^{uam} - \lambda_{i1k}^{uam})$$

We can note that several terms not involving a(j) are zero. Also when the second coefficient is subtracted from the first, the difference always equals twice the value of the first as a result of the constraints. Thus to obtain the the coefficients of a logit model from an appropriate log-linear model, we can double the coefficients of those terms in the log-linear equations which involve the dependent variable, and disregard the others (Swafford 1980).

Thus the logit model is a special case of the general log-linear model where the parameters λ_i^u, λ_k^m and λ_{ik}^{um} associated with the explanatory

variables u and m are considered fixed. Like the classical quantitative regression model, the logit model expresses a conditional relationship between the response variable a and fixed values of the explanatory variable u and m. The terms represent associations of dependent variable with others, conditioned on all possible associations among independent variables. It can be noted that the above model is still the saturated model (UAM). But other non-saturated logit models can be easily formulated in the similar way.

Estimation

Estimation of the log-linear models was done by BMDP-4F program. Estimation of log-linear models always fits exactly the marginal totals corresponding to main effects and interaction terms in the model. This is necessary and sufficient for m_{ijk}'s to be maximum likelihood estimates under the model. For small-dimensional tables and simple models, this may be done *directly*. On the other hand, some models can not be solved explicitly, but can be fitted iteratively. The iterative proportional fitting algorithm is used.

Both the direct fitting and iterative proportional fitting of $\hat{m}$ give the MLE of the *m under the given model*, i.e. conditional on its appropriateness. Thus $\hat{m}$'s are consistent with minimum sampling variance. Given that the $\hat{m}$'s are MLE's, the $\hat{\lambda}$'s are also MLE. It is due to the fact that any monotonic transformation, e.g. log $\hat{m}$, and linear combinations of MLE are also MLE. That is, $\hat{\lambda} = 1 / IJK \sum \ln m_{\hat{ijk}}$.

A logit model has A as dependent variable, U and M as independent variables. A model with no interaction effect is run to show the equivalence of log-linear model and logit model empirically. For this purpose, it is estimated by BMDP-LR program which uses the maximum likelihood estimation. Specifically, employment status is indicated by the dummy variable UNEMPLOY. For the mother's smoking history with 3 categories, two dummy variables. MOMNEVER and MOMSTOP, are used. The baseline group is those whose mother is not smoking currently. People with non-smoking mothers are divided into two groups, i.e. one group where mothers never smoked, and the other group where mothers smoked, but quit. These effects, in comparison with the basegroup of non-smoking

mothers, will be represented by the coefficients of two dummy variables, i.e. MOMNEVER and MOMSTOP.

RESULTS

All possible models to be compared were estimated. The results are summarized in table 3. Column one shows the model specification in the conventional form. As mentioned before, models are hierarchical in that higher interaction term indicates inclusion of all lower order interactions. The saturated model is in the last row, and indicated by (UAM).

〈Table 3〉 Results from Hierarchical Log-Linear Models

Model	x^2	d.f.	p-value	Realism	Parsimony
(A)	122.40	10	.00		
(M)	107.57	9	.00		
(U)	79.01	10	.00		
(M)(A)	84.31	8	.00		
(U)(A)	55.75	9	.00		
(U)(M)	40.92	8	.00		
(U)(M)(A)	17.66	7	.01		
(AU)	48.32	8	.00		
(UM)	35.02	6	.00		
(AM)	83.00	6	.00		
(U)(MA)	16.35	5	.01		
(M)(AU)	10.23	6	.11	#	
(A)(UM)	11.76	5	.03		
(MA)(MU)	10.45	3	.01		
(MA)(UA)	8.92	4	.06	#	
(UA)(UM)	4.34	4	.36	#	#
(UA)(UM)(MA)	1.99	2	.37	#	
(UAM)	.00	0	1.00	#	

* x^2 is the likelihood ratio statistic.

** The cutpoint for realistic model is .05.

*** Parsimony is tested at the .05 level from the previous model.

The fit of the model can be tested using either the usual Pearson goodness-of-fit chi-square statistic

$$x^2 = \sum (X_{ijk} - m_{ijk})^2 / m_{ijk}$$

or the likelihood ratio statistic

$$G^2 = 2\sum X_{ijk} \ln(X_{ijk} / m_{ijk})$$

where X_{ijk} is the observed cell frequency. Both are asymptotically distributed as chi-square, with n-p degrees of freedom, where n is the number of cells, and p is the number of independent parameters estimated. The likelihood ratio statistic G^2 is additive under partitioning for nested models. Two models are said to be nested if all of the λ's effects in one model are a subset of the λ's in the other model. The difference in G^2 also has an asymptotic chi-square distribution with the degree of freedom equal to the difference in the number of parameters fitted to the two models. This property does not hold for the Pearson chi-square. Thus the likelihood ratio chi-square is reported and used for the test. Column 2 and 3 provides the x^2 statistic and the degree of freedom for each model. The p-value associated with these values for each model is in the column 4.

In general, there are two criteria for screening models among various potential models. The first criterion will be the realism or explanation. A model should be able to explain the observed phenomenon or data. By this criterion, we choose among variables that provide adequate fit to observed data. This can be done by the x^2 test with the information in column 2 to 4 in table 3. In this study, the cutpoint .05 level is used for the realistic model criterion. Five models turn out to meet this requirement, i.e. (M)(AU), (MA)(UA), (UA)(UM), (UA)(UM)(MA), and (UAM).

The second criterion will be parsimony. A model is a simplified representation of the reality, not the exact description of the reality. Thus simplicity becomes the virtue of a model, as is brevity in writing. By this criterion, among realistic models, i.e. models that give adequate fit, we choose more complex models over simpler ones only when they significantly improve the fit to data. This can be done by the x^2 difference for nested models. For example, both (M)(AU) and (MA)(AU) are realistic, and they are nested ones. The former model has x^2 (6) = 10.23, where as the latter model has x^2 (4) = 8.92. The x^2 difference is 1.31 with d.f. 2. So the improvement in fit from simpler model (M)(AU) to more complex model (MA)(AU) is not sig-

nificant. Thus the simpler model (M)(AU) is preferred to the more complex model (MA)(AU). According to realism and parsimony criteria, model (UM) seems to be appropriate. However, these are all based on the data considerations. We should use *substantive theory* to discriminate among several models. Especially when there are several models that meet both realism and parsimony but are non-nested, this will be crucial. But the substantive theory should be always used in guiding the study as well as in selecting the model. This issue will be examined in the discussion section. Table 4 provides the summary of key results from the model (AU)(UM).

〈Table 4〉 Results from Log-Linear Model(AU)(UM)

	Likelihood-Ratio		Pearson	
D.F.	x^2	p	x^2	p
4	4.34	0.36	4.32	0.36

UNEMPLOY

EMPLOYED	UNEMPLOYED
0.767	−0.767

MOMHIST

SMOKING	QUIT	NEVER SMOK
−0.319	−0.672	0.811

ABSTIN

RELAPSE	ABSTINENCE
−0.232	0.232

	UNEMPLOY	
MOMHIST	EMPLOYED	UNEMPLOYED
SMOKING	−0.073	0.073
QUIT	0.374	−0.374
NEVER SM	−0.302	0.302

	UNEMPLOY	
ABSTIN	EMPLOYED	UNEMPLOYED
RELAPSE	−0.259	0.259
ABSTIN	0.259	−0.259

It has been shown that in a saturated model, the $\hat{\lambda}$ terms have a norma distribution with mean λ and calculable variances (Goodman 1971). This re sult is asymptotic and limited to the saturated model. Many programs, in cluding BMDP, give the standard error for any model calculated as thoug the model was saturated. This calculation is done by so-called "delta method" (Bishop et al. 1975). In selecting and testing the model, x^2 criterio is preferred to the standard error since there are several problems wit standard error. First, standard error is strictly correct only for saturate models. So it can not be generally used to examine terms for possible ex clusion from models, unless the resultant model is close to saturated one Second, $\hat{\lambda}$ terms may differ quite a bit from saturated to simpler models while variances do not. Third, $\hat{\lambda}$ terms are in general fairly highly correlate with each other, both across categories and interactions with other variables Thus these should not relied upon so much.

The results for the logit model is reported in table 5. The overall model fi can be assessed by the log likelihood ratio x^2. -2lnL has an asymtotic x^2 wit d.f. N-p, where N is the sample size and p is the number of parameters Here it is 216.51 with d.f. 176. The p-value is .06, suggesting that the mode provides the acceptable fit. In order to check the equivalence of the result by log-linear modelling, this is run also by the log-linear model. The corre sponding model in the context of general log-linear models is (AU)(AM (MU), and the results by BMDP-4F are summarized in table 6.

〈Table 5〉 Results from Logit Model

LOG LIKELIHOOD= −108.251

GOODNESS OF FIT CHI-SQ (2*0*LN(0/E)= 1.991 D.F = 2 P-VALUE=0.369
GOODNESS OF FIT CHI-SQ (D.HOSMER)= 0.391 D.F = 2 P-VALUE=0.822
GOODNESS OF FIT CHI-SQ (C.C.BROWN)= 2.012 D.F = 2 P-VALUE=0.366

TERM	COEFFICIENT	STANDARD ERROR	COEFF / S.E.
UNEMPLOY	−0.568	0.196	−2.901
MOMSTOP	0.059	0.240	0.244
MOMNEVER	0.278	0.197	1.412
CONSTANT	0.449	0.240	1.871

〈Table 6〉 Results from Log-Linear Model(AU)(AM)(UM)

UNEMPLOY		ABSTIN	
EMPLOYED	UNEMPLOYED	RELAPSE	ABSTINENCE
0.779	−0.779	−0.168	0.168

	MOMHIST	
SMOKING	QUIT	NEVER SMOK
−0.121	−0.659	0.780

	UNEMPLOY	
MOMHIST	EMPLOYED	UNEMPLOYED
SMOKING	−0.043	0.343
QUIT	0.388	−0.388
NEVER SM	−0.346	0.346

	UNEMPLOY	
ABSTIN	EMPLOYED	UNEMPLOYED
RELAPSE	−0.284	0.284
ABSTINEN	0.284	−0.284

	MOMHIST		
ABSTIN	SMOKING	QUIT	NEVER SMOK
RELAPSE	0.112	0.054	−0.166
ABSTIN	−0.112	−0.054	0.166

We can note several points by comparing two tables. First, we can note that logit run by BMDP-LR provides the goodness of fit x^2, 1.991 with d.f. 2, which is the G^2 statistic from the log-linear model by BMDP-4F. Second, we can find that twice the corresponding λ's in table 6 are equal to the coefficients of logit model in table 5. For example, λ_{ij}^{ua} is −.268, and the coefficient of UNEMPLOY is −.568. So we can confirm the algebraic equivalence which was shown already. Other possible logit models are (AU)(UM),

(AUM) etc. These were already run, and reported in table 3. So we can compare the nested models which are realistic. (AUM) is the saturated model, and there is no significant improvement from (AU)(AM)(UM). But (AU)(UM) has x^2 4.34 with d.f. 4. So the improvement by including the term (AM) is not significant. So (AU)(UM) seems to be the best logit model in the general log-linear model notation.

DISCUSSION

We have chosen the model (AU)(UM) as both parsimonious and realistic one. Thus H1 is supported. We can say that abstinent behavior is associated with one's employment status. However, H2 seems to be less supported. Though the model (AU)(UM)(AM) is realistic with x^2 1.99 with 2 d.f., the improvement of fit over (AU)(UM) is not significant. (AU)(UM) has the x^2 4.34 with d.f. 4, and the x^2 difference is only 2.45 with d.f. 2, which is not significant (see table 3). So we can conclude that there seems to be little evidence showing the association between abstinent behavior and mother's smoking history.

Let us turn to interpreting several models. (AU)(M) is a partial independence model. M is independent of A and U, which are themselves associated. So abstinent behavior is associated with employment status, but mother's smoking history is independent of either of the two. On the other hand, (AU)(UM) is a conditional independence model. A and M are independent at each level of U, with which both are associated. Thus abstinent behavior and employment status are associated and employment status and mother's smoking history are associated. But at each level of employment status, abstinent behavior and mother's smoking history are independent.

If we look at the bi-variate level, A and M seems to be associated. But this is a spurious relationship which disappears by including U. Since both A and M are associated with U, they might look associated with each other. But they are not associated when they are conditioned on the level of U. Thus H2 might have obtained the spurious support if we had investigated the data at the bi-variate level. But that is an artifact of not including the related variable, here U. This is similar to the third variable explanation phenom-

enon for the spurious correlation. Thus we can not say that H2 is supported.

An interesting, but important, point seems to emerge. Even if our research hypothesis is about the relationship between two variables, e.g. A and U, it is not sufficient to look at just two variables. We need to control for other variables which might affect the relationship. In the context of regression, this will be similar to misspecification error like excluding the relevant variables. Then the resulting estimates will be biased, and misleading. What we need is the partialed-out effect of a variable.

Model (AU)(AM)(UM) is all first-order interaction model. All pairs are independently associated, and these associations do not vary with level of a third variable. This can be understood as the logit model where dependent variable is A and two independent variables are U and M. (AU) and (AM) will correspond to the dependence relationships between the dependent variable and independent variables, while (UM) is to account for the background correlation among independent variables. We have already shown that (AM) is not significant by comparing this model with the nested model (AU)(UM).

This can be also done by looking at the results by logit run. If we look at table 5, we can see that UNEMPLOY has the t-ratio of −2.90. This is significant, and suggests that (AU) is significant. In other words, H1 is supported also by this result. But the t-ratios for mother's history are not significant. Specifically, the t-ratios for MOMNEVER and MOMSTOP are 1.41 and .244 respectively. In general, there seems to be little association between mother's history and abstinence behavior.

The coefficient of UNEMPLOY is −.568. Thus the unemployed are more likely to relapse to smoking than the base group, i.e. the employed. If we look at the coefficients of MOMNEVER and MOMSTOP, the coefficient of MOMNEVER .278 with the t-ratio 1.41, and that of MOMSTOP is .059 with .244. These are the difference from the baseline group, i.e. the group with smoking mothers. Mothers who never smoked seem to help the female ex-smokers maintain abstinence. But mother's quitting behavior after smoking experience seems to have little influence on female ex-smoker's abstinent behavior. However, this is of less use since the coefficients are not statistically significant. Though they are in the expected sign, they do not reach statistical significance.

What are the underlying mechanisms behind the association between the employment status of the female ex-smoker and the long-term abstinent behavior? What we have shown is the input and output relationship or structural one. However, in order to explain, predict and control a phenomenon, we need to understand the processes underlying phenomenon. The intermediating variables or processes are not clearly shown by this approach. It is not an easy question since employment status is quite a broad concept which is related to many other variables. Within the data limitations, some explanations will be examined. Some explanations will be also suggested, though not tested. Possible directions for testing those conjectures will be discussed.

One explanation might be that the unemployed females are mostly housewives and they might have less self-efficacy than the employed who might have more confidence in their ability. Then the underlying variable is the self-efficacy in this explanation. If this is the explanation for the significant relationship between employment status and abstinence behavior, then the effect should disappear when we include the self-efficacy in the model.

A logit model with the self-efficacy included was run. Above explanation is supported *and* unsupported. This is supported in the sense that self-efficiacy is one of the significant predictors. Thus self-efficacy is associated with the abstinence behavior. But it is not supported in the sense that still the variable UNEMPLOY in the model with the self-efficacy included has a significant effect. If the observed association between the employment status and the abstinent behavior had been the result of the differential self-efficacy between the employed and unemployed, then the effect of UNEMPLOY should have become insignificant by including the self-efficacy variable. But this was not the case here. So we can say that self-efficacy alone does not explain the association between employment status and the abstinent behavior.

Another explanation might be that the work place serves as the constraints or pressure against smoking. To the extent that work place is public and that no smoking is allowed in many public places, the employed persons will have fewer chances for smoking. This might help them fight against the urge to smoke. Also the public and non-smokers might be covert pressure against smoking, though smoking is allowed at the work place. Some desirability such as non-smoking female as an ideal female or good

breath might be stronger for the employed females. These will lead to the observed finding that the employed tend to keep more abstinent than the unemployed. This can not be tested by the current data set. We might need some more measures about these factors, which might be used as indicators of the pressure against smoking or constraints.

If we obtain more data on such variables in continuous scale, we could apply the path analysis or causal modelling by LISREL. LISREL model has the advantages such as considering the measurement errors, use of multiple indicators, bridging the conceptual and empirical worlds etc. But the input data are the variance-covariance matrix, and the variables need to be measured in interval scale. Also the multivarite normality is the needed for the data. However, Joreskog and Sorbom claim that if the distribution of the observed variables are moderately non-symmetric, the ML method may still be used to fit the model (Joreskog and Sorbom 1984: chap 4 for analysis of discrete variable). This will might help us do confirmatory analysis of the observed associations or causal modelling of the underlying processes.

Another potential area for research might be breaking down the occupations, and see whether there is any significant pattern of effects due to the type of job. For example, people in the professional job are expected to keep more abstinence. While we have shown the existence of the relationship between employment and abstinence, the in-depth analysis can be done in this way. Thus we call perform the log-linear model analysis within the employed by categorizing into several different occupation groups. This will lead to further insights into the phenomenon.

On the other hand, the hypothesized reference group effect was not found. Social comparison theory predicts that one might use the person who is similar and and near to one as the comparison person. Mother might be similar to the female-ex-smoker, but might not near to her. Considering that many people do not live with their parents, they are less likely to be influential. Thus it is possible that mothers living with the subjects have influence on the abstinent behavior of their daughters, while those not living together might not. In order to test this, we can analyze the data separately for each group,and compare two groups. But this is not available in this data set, and can be examined in future study. Alternatively, smoking might have become so personalized habit that it is not really affected by the others' behavior.

This is the rejection of the reference group hypothesis, whereas the above explanation still suggests the existence of reference group effect on smoking, but to a different degree.

Some potential problems with the current study are examined below. There were no zero cell problems in this analysis. There were no structural zeros where particular combinations of classifications are logically impossible or missing by the features of the design. Also there were no random zeros where potential conditions of classifications are possible but not observed in a given sample. But there is a potential problem with sparse expected cell. x^2 is unreliable when many cells have expected values less than 5 (Knoke and Burke 1980). In the final model (AU)(UM), there are four cells with less than 5 expected cell size. And the minimum expected cell size was 1.5. This might lead to the unreliable results on the statistic like x^2 etc.

To raise the expected cell counts, we can combine categories. But this aggregation should not distort the relationship. Here the option of collapsing the group with mothers who quit and the group with mothers who never smoked was initially considered. But the test all the suitable shows that collapsing is not appropriate. Thus aggregation was not done to the data. On the other hand, some researchers claim that 5 requirement is too conservative, and cell expectations greater than 1 are probably good enough to trust the results. In that sense, the problem might not be so serious.

While we test the overall model fit to the data by x^2, we can check the departure of the model by examining the deviations. The standardized deviates are approximately standard normal for each cell, where they are obtained by

$$Z_{ijk} = \frac{(X_{ijk} - m_{ijk})}{\sqrt{m_{ijk}}}$$

We can note that these are the square root of the components used in computing the x^2 statistic. The largest value is 1.2, and that would be expected by chance at .05 level. Thus the departure seems to be not significant. Also BMDP-4F provides the Freeman-Tukey deviates. These are similar to Z score when the data are from the Poisson distribution. The largest Freeman-Tukey deviate deviate is 1.2, and seems to be non-significant.

SUMMARY

Log-linear models were used to analyze the categorical data on female ex-smokers. The variables were one's employment status, mother's smoking history, and the long-term abstinent behavior. By comparing the hierarchical models, we found that the conditional independence model (AU)(UM) is the best by the criteria of realism and parsimony. H1 is therefore supported, and there is evidence that shows the association between employment status and the abstinent behavior. The need for the investigating the underlying processes was emphasized, and some possible explanations were suggested. H2 is, however, not supported. A related issue of bi-variate analysis vs. multi-variate analysis and the spurious association was also mentioned. When conditioned on employment status, mother's smoking history and abstinent behavior seem to be independent. The evidence is not sufficient to support that there is an association between mother's smoking history and female ex-smoker's abstinent behavior.

We have also shown that logit model is a special case of the general log-linear models. The algebraic equivalence was shown first, and the estimation results were compared to show the empirical equivalence. Thus log-linear analysis is a powerful method for finding "what is related to what", and it can investigate the relationships among variables. The categorical data are frequent in the social science research, but they are not adequate for usual quantitative analysis which assumes the interval scale. Log-linear model has the advantage of naturally reflecting the categorical nature of such data. In logit model, however, we are interested in a dependent variable to be explained. Here long-term abstinent behavior of the female ex-smoker is the dependent variable. The structure of the model implicitly assumes the causal relationship between the abstinent behavior and independent variables. But it may be noted that we can not prove the causal relationship, but only infer causality from the observed association.

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