Using Latent Transition Analysis to Test the Gateway Hypothesis of Drug Use Onset in the Add Health Data

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Abstract

According to the Gateway Hypothesis, the use of one substance serves as a gateway for another, more advanced substance. In general, researchers investigating the Gateway Hypothesis (e.g. Collins, in press; Kandel & Faust, 1975; Kandel & Yamaguchi, 1993) have found that legal substances, such as tobacco and alcohol, serve a gateway function for marijuana use, which in turn serves as a gateway for cocaine. Collins (2002) discusses two testable conditions implied by the Gateway Hypothesis: (1) there is an order by which people try substances, such that the gateway substance precedes other substances; and (2) a gateway substance is associated with increased risk of more advanced substance use. Both of these criteria must be met in order for the gateway relation to hold. In the present report, the National Longitudinal Study of Adolescent Health (Add Health) dataset was used to evaluate the role of marijuana as a gateway drug for cocaine and the role of cigarettes as a gateway for drunkenness and marijuana. The Latent Transition Analysis (LTA) framework outlined by Collins (2002) was used to perform this series of gateway hypothesis tests. Analyses of the data suggest that marijuana is a gateway for cocaine. Having tried marijuana precedes the use of cocaine and increases the risk for trying cocaine. However, the analyses suggest that cigarettes are not always a gateway for drunkenness and marijuana.

Introduction

Although the majority of adolescents do not abuse drugs, a significant minority do. Different motivations (e.g. curiosity, a desire for sensation, peer pressure, desire to escape from overwhelming problems) can lead adolescents to try alcohol, cigarettes or marijuana, which are the most popular drugs among adolescents. These drugs are sometimes called gateway drugs because their use often is eventually followed by use of more additive substances, such as cocaine. Because of the potential danger of substance use involvement to adolescents' physical and psychological health, substance use onset has been a focus of study when evaluating negative outcomes among adolescents. The notion of stages of substance use underlies a crucial component of a life course approach examining patterns of drug use involvement (Kandel, 1989).

Gateway Hypothesis

Stages of substance use involvement representing different substances have been identified in several empirical studies (Kandel & Faust, 1975; Yamaguchi & Kandel, 1984a,b; Kandel, 1988; Kandel & Yamaguichi, 1993). The Gateway Hypothesis is an example of a stage sequential framework for studying the progression of substance use. According to the Gateway Hypothesis, it is necessary to go through some gateway drugs in order to reach the more advanced substances. Gateway drugs are those substances that precede and increase the risk of trying more advanced drugs. Thus the Gateway Hypothesis predicts that there is ordering of participation in stages of drug use involvement. For example, researchers have found that legal drugs (e.g. alcohol and tobacco) appear as gateways for more advanced substances (Kandel & Faust, 1975; Yamaguchi & Kandel, 1984a,b; Kandel, 1988; Kandel & Yamaguichi, 1993). In other words, the use of legal substances (i.e. alcohol and cigarettes) precedes and increases the risk of initiating the use of illicit drugs. The Gateway Hypothesis proposes that adolescents

are very unlikely to experiment with marijuana if they have not experimented previously with alcoholic beverages or with cigarettes. It also predicts that trying cocaine is very unlikely without having first tried marijuana.

Empirical research has suggested that the onset process usually starts with alcohol, with individuals going on either to try cigarettes and then have a first experience with drunkenness, or to have a first experience with drunkenness followed by trying cigarettes (Graham, Collins, Wugalter, Chung, & Hansen, 1991; Collins, Graham, Long, & Hansen, 1994; Collins, Graham, Rousculp, & Hansen, 1997; Collins, Hyatt & Graham, 2000; Hyatt, Collins, & Graham, 2000). However, a small subset of individuals start their substance use experience with cigarettes followed by alcohol and then drunkenness. These researchers have also found that marijuana came next, followed by cocaine.

Collins (2002) argued that the Gateway Hypothesis makes two testable implications. The first implication of this hypothesis is that there is an order by which people try substances, such that the gateway drug precedes the other substance. The second implication of this hypothesis is that a substance is not a gateway just because it precedes another. Instead, a gateway drug must also be associated with increased risk for more advanced substance use. According to Collins (2002), these conditions must be met in order for a substance to be considered a gateway for another substance.

The present study

The present study provides an empirical test of the Gateway Hypothesis using Latent Transition Analysis (LTA). LTA (Collins & Wugalter, 1992) has many potential uses in the field of human development and prevention. It can be used to estimate stage-sequential models of individual development in longitudinal data, such as the models predicted by the Gateway Hypothesis. The analysis presented in this paper will show how LTA can be used to examine

three particular gateway hypotheses: (1) marijuana is a gateway for cocaine, (2) cigarettes are a gateway for drunkenness, and (3) cigarettes are a gateway for marijuana.

The logic behind the models tested here is as follows. Let us take the example of marijuana as a putative gateway for cocaine. If marijuana is a gateway for cocaine, then according to the Collins (2002) interpretation of the Gateway Hypothesis (a) trying marijuana must precede trying cocaine, and (b) trying marijuana must put an individual at increased risk for trying cocaine. Consider the hypothesis that marijuana is not a gateway for cocaine. Under this hypothesis, there will be individuals who have tried cocaine without having first tried marijuana. Thus a model constructed to test this hypothesis must include stages with the following characteristics: marijuana use without cocaine use, cocaine use without marijuana use, and marijuana and cocaine use. Now consider the hypothesis that marijuana is a gateway for cocaine. A model constructed to test this hypothesis would not need a stage characterized by cocaine use without marijuana use under this hypothesis, because according to this hypothesis everyone who has tried cocaine has tried marijuana first. Such hypotheses can be examined in empirical data by fitting a model including all three stages. If the gateway hypothesis holds, the Tried Cocaine Only stage is unnecessary and will be virtually empty. Once the appropriate stages in a model have been determined empirically, it is possible to examine stage transitions over time to determine whether the requirement of increased risk holds.

Substance use model. The first model tested in the present study, Model 1, was a baseline model of substance use onset drawn from previous analyses of the Add Health data reported in Hyatt and Collins (1999). This study concluded that Model 1 is a reasonable representation of the Add Health data set. In Model 1, the circles represent stages in the model and the arrows represent possible stage transitions. This model is characterized by nine drug use latent status: (1) no drug use, (2) experimentation with alcohol only (denoted A in Model 1),

(3) experimentation with cigarettes only (C), (4) experimentation with alcohol and cigarettes (AC), (5) cigarettes and marijuana (CM), (6) alcohol, cigarettes and drunkenness (ACD), (7) alcohol, cigarettes and marijuana (ACM), (8) alcohol, cigarettes, drunkenness and marijuana (ACDM), and (9) alcohol, cigarettes, drunkenness and marijuana, and cocaine (ACDMcoc). According to Model 1, the early part of the onset process involves several alternative paths: either alcohol first, then being drunk, then cigarettes; or alcohol first, then cigarettes, then drunkenness. From this point, the next substance tried is marijuana, followed by cocaine. Model 1 omits the stage that would be necessary if marijuana is *not* a gateway substance for cocaine (ACDcoc). This model also excludes the stage that would be necessary if cigarettes are *not* a gateway for drunkenness (AD) and if cigarettes are *not* a gateway for marijuana (M, and AM).

Marijuana as a gateway for cocaine. Model 2, represents the hypothesis that marijuana is not a gateway for cocaine. Model 2 is exactly the same as Model 1 with the addition of an alcohol, cigarettes, drunkenness, and cocaine (ACDcoc) stage. As discussed above, if marijuana is *not* a gateway for cocaine then we would expect to need the ACDcoc stage. If marijuana is a gateway substance for cocaine, there will be stages involving trying marijuana without having tried cocaine (ACDM), but no stages involving having tried cocaine without having tried marijuana (ACDcoc). On the other hand, if cocaine is a gateway for marijuana, there will be stages involving trying cocaine without having tried marijuana but no stages involving trying marijuana without having tried cocaine. If there is no ordering between the substances, either substance may be tried first, and both stages will be observed in approximately equal frequency. If Model 2 fits the data better than Model 1, this is evidence against the hypothesis that marijuana is a gateway for cocaine.

Cigarettes as a gateway for drunkenness and marijuana. Model 3, represents the hypothesis that cigarettes are not a gateway for drunkenness and marijuana. Model 3 is exactly the same as Model 1 with the addition of the AD, M, and AM stages. If cigarettes are *not* a gateway for drunkenness then we would expect to need the AD (alcohol + drunkenness) stage. If cigarettes are not a gateway for marijuana then we would expect to need the M (marijuana only) and AM (alcohol + marijuana) stages. If Model 3 fits the data better than Model 1, this is evidence against the hypothesis that cigarettes are a gateway substance.

Method

Participants

Participants were included from Waves I and II of the *National Longitudinal Study of Adolescent Health* (Add Health;Resnick et al., 1997). The Add Health is a school-based study of the health-related behaviors of adolescents in grades 7-12 exploring the causes of these behaviors, emphasizing social context influences. The first wave of data included students in grades 7 through 11 who were interviewed between April and December 1995. The second wave included the same subjects interviewed again between April and August 1996.

The contractual set of the Add Health data was used for this project. Students who were in 9th, 10th and 11th grade at Wave I were included. The first cohort (9th grade at Wave I and 10th grade at Wave II) included 2066 students (mean age 15.5 years old). The second cohort (10th grade) included 2019 student (mean age 16.5 years old), and the third cohort (11th grade at Wave) included 2073 students (mean age 17.4 years old). Thus for the analyses reported here, 6158 students (48.6% females and 51.4% males) were included.

Measures

Grade. A single manifest variable was used to measure the grade in which participants were at Wave I. Responses were coded as 1 for 9th grade, 2 for 10th grade, and 3 for 11th grade.

Substance use. Six items were used to measure an individual's level of substance use at each year. The first four items measured lifetime alcohol, lifetime cigarettes, lifetime marijuana, and lifetime cocaine use. Responses on these items were coded as 1 for "never used" and 2 "used once or more". The remaining two items were used to measure drunkenness and were coded as 1 for "never past in 12 months" and 2 for "one day or more in the past 12 months". Exact wordings of the original items are reported in Table 1.

Missing data

LTA's maximum likelihood missing data routine was used to deal with any missing items for the participants and analyses were conducted on all subjects. For this project, the models represent lifetime substance use; therefore, participants who responded they have "used once or more" to any of the substance use items (i.e. lifetime alcohol, lifetime cigarettes, lifetime marijuana, and lifetime cocaine use) at Time 1 were coded as "used once or more" at Time 2. For example, if a participant responded they have "used once or more" to the alcohol item at Time 1, then the response to the alcohol item at Time 2 was also recoded as "used once or more".

For the alcohol item, less than one percent of the participants had a missing value at Time 1 (n=54), and 5% of the cases had a missing data at Time 2 (N=309). For cigarettes lifetime use, less than one percent of the participants had a missing value at Time 1 (n=59), and 5% of the cases had a missing data at Time 2 (N=308). For the drunkenness items, the amount of missing data ranged between 12%-15% at Time 1 and 23%-25% at Time 2. For the marijuana use item, 2% of the participants had a missing value at time 1 and 9% at Time 2

(n=554); and for the cocaine item, 2% were missing at Time 1 and 12% were missing at Time 2 (n=752).

Analytical Procedure

Latent Transition Analysis (LTA) is used to fit a proposed model to data by examining stage-sequential dynamic latent variables in longitudinal data. This procedure can estimate: a) the probability of membership in each latent class (latent classes are groups in the static part of the model), b) the probability of membership in each latent status at each time (latent statuses are stages in the dynamic part of the model), and c) the transition to a different latent status between consecutive times. Both latent classes and latent statuses can be measured by multiple categorical items. In the analyses conducted in this project, the latent class is the grade in which participants were at Wave I (9^{th}, 10^{th} or 11^{th}), and the dynamic part of the model is substance use onset.

Mathematical Model. For the purpose of this project, the LTA mathematical model is presented in terms of the models to be tested here as we examine the Gateway Hypothesis of substance use. All the models examined in this project include one manifest indicator of the static latent variable (i.e. grade), and six manifest indicators of the latent statuses (i.e. alcohol, cigarettes, two items for drunkenness, marijuana and cocaine) involved in substance use onset at each time.

The static latent variable (i.e. grade) divides the sample into $c=1,\ldots, C$ classes. In this case $c=3$. Furthermore, in this example the classes are not technically latent, as grade is observed without error. The latent classes are measured by only one manifest indicator, with $a=1,\ldots, A$ response categories. The six manifest indicators of the dynamic latent variable,i.e. the alcohol, cigarettes, marijuana, and cocaine items, plus two items for drunkenness, are

measured at two time points, Time 1 and Time 2. Item 1 has *i, i'*=1,…, *I* response categories, Item 2 has *j ,j'*=1,…, *J* response categories, and so on, where *i, j, k, l, m,* and *n* refer to item responses at Time 1 and *i', j', k', l', m',* and *n'* refer to item responses at Time 2. Let *p*=1,…,*S* denote the latent statuses at Time 1 and let *q*=1, …, *S* denote the latent statuses at Time t+1. For example, in Model 1, *S*=9.

Let *Y* = {*a,i,j,k,l,m,n,i',j',k',l',m',n'*} represent a response pattern, that is, a set of possible responses to the array of items. Then,

P(*Y*) =

$$\sum_{c=1}^{C}\sum_{p=1}^{S}\sum_{q=1}^{S}\gamma_c\rho_{a|c}\delta_{p|c}\rho_{i|p,c}\rho_{j|p,c}\rho_{k|p,c}\rho_{l|p,c}\rho_{m|p,c}\rho_{n|p,c}\tau_{q|p,c}\rho_{i'|q,c}\rho_{j'|q,c}\rho_{k'|q,c}\rho_{l'|q,c}\rho_{m'|q,c}\rho_{n'|q,c}$$

where,

γ_c is the probability of being in latent class *c (*e.g. probability of being in 9th grade at Time 1)*;*

$\rho_{a|c}$ represents the probability of having the value *a* on the indicator of latent class membership, conditional on membership in latent class *c* (e.g. probability of responding "in 9th grade" conditional on membership in 9th grade latent class. In the models tested here, these parameters are fixed to 0 or 1, as described below.);

$\delta_{p|c}$ is the proportion in latent status *p* at Time 1 conditional on membership in latent class *c*; that is the proportion of latent class *c* members whose latent status is *p* at Time 1 (e.g. proportion of 9th graders whose latent status is " Alcohol Only" Time 1);

$\rho_{i|p,c}$ represents the probability of response *i* to Item 1 at Time 1, given membership in latent status *p* at Time 1 and membership in latent class *c* (e.g. the probability of responding "No" to the alcohol use item at Time 1, given membership in the "No Use" latent status and

membership in 9th grade); similarly, $\rho_{i'|q,c}$ represents the probability of response *i'* to Item 1 at Time 2, given the membership in latent status *q* at Time 2 and membership in latent class *c;*

$\tau_{q|p,c}$ is the probability of membership in latent status *q* at Time 2 given membership in latent status *p* at Time 1 and membership in latent class *c* (e.g. the probability of being in the "Alcohol Only" latent status in 10th grade, given membership in the "No Use" latent status one year before).

Identification and Constraints. In order to eliminate problems with identification and aid in model specification and interpretability, the number of parameters estimated must be reduced by either fixing or constraining parameters. In the analyses reported here, the γ parameters and the δ parameters were estimated freely. The τ parameters, which make up the transition probability matrix, had the same pattern of parameter restrictions for each latent class. Illogical transitions between latent statuses were set to zero (e.g. having tried alcohol and cigarettes at Time 1 and transitioning to never having tried any substances at Time 2). All logical transitions were freely estimated (e.g. not having tried any substances at Time 1 and transitioning to having tried alcohol and cigarettes at Time 2). Table 2 show the parameter restrictions for the τ parameters for Models 1, 2, and 3, respectively.

The ρ parameters associated with the items measuring the static variable (often referred to as "little rho's", grade, were fixed because only one item was used to evaluate the static part of the model. The ρ parameters for the dynamic latent variable (often referred to as "big rho's", substance use, were constrained to be equal across time and across latent classes, so that the meaning of the latent statuses remains the same across times and grades. Restricting the big rho's (ρ) in this way reduces the number of parameters to be estimated considerably, and also aids in interpretation of the transition probabilities. In addition, constraints were imposed so that

only two ρ parameters were estimated for each of the six latent status items: one for the probability of responding "yes" when a "yes" was expected, and one for the probability of responding "no" when a "no" was expected.

Estimation and Missing Data Procedure. WinLTA software was used to perform the analyses reported here. WinLTA performs maximum likelihood estimation by means of the EM (Expectation-Maximization) algorithm (Dempter, Laird & Rubin, 1977; Goodman, 1974). When individuals do not respond to all of the items used to determine latent class/status, WinLTA uses computational techniques that have been developed to handle incomplete data in contingency tables (Schafer, 1997). In addition, Hyatt & Collins (1998) suggested that WinLTA's procedure for handling missing data was robust when the probability of nonresponse to one or more items was unrelated to any of the variables in the analysis (i.e. missing completely at random), or predicted by variables included in the analysis (i.e. missing at random).

Model selection fit indices

Model selection in this study was based on Akaike's Information Criterion (AIC) and the Bayesian Information Criteria (BIC). The goal of these indices is to help the user pick the one model from several competing ones that will hold up best under replication. The AIC index is made up of the model fit chi-square, which is –2 times the log of the likelihood L, plus a penalty for each freely estimated parameter p. The BIC index is similar, except that this uses a different penalty. Despite a superficial similarity between the AIC and BIC, the latter is derived in a very different way and within a Bayesian framework (Zucchini, 2000). The AIC and BIC can be expressed as follows:

$$AIC = -2 \log (L) + 2p$$

$$BIC = -2 \log (L) + p \log(n)$$

The BIC differs from the AIC only in the second term, which now depends on the sample size *n* as well as on *p*. Clearly, as *n* increases, the BIC favors simpler approximating families (that is families with a smaller number of parameters *p*) than does the AIC. The AIC favors models that have neither too many nor too few free parameters. When entertaining several models, the decision strategy is to pick the one with the smallest AIC and BIC value. Models containing too few free parameters are penalized because of their large fit chi-square. Also, models containing many redundant parameters are penalized. The idea is that redundant parameters add little more than random noise to a model, and thus render the set of parameter estimates less replicable. If the BIC and AIC disagree, it is customary to select the more parsimonious model (Collins, Graham, Long, & Hansen, 1994).

Results

The results from estimating and testing Model 1 (Substance Use Onset Model) will be reviewed, followed by a comparison of Model 1 vs. Model 2 (marijuana as a gateway for cocaine) and Model 1 vs. Model 3 (cigarettes as a gateway for drunkenness and marijuana).

Substance Use Onset Model
(Model1)

Table 5 shows that the value of the G-squared fit statistic associated with Model 1 is less than the degrees of freedom, which suggests that the model fits the data reasonably well. Table 6 reported the ρ parameter estimates for Model 1. These parameters suggests that the probability of answering "yes" to each item given latent status membership is greater than .8 or less .2 for all items, indicating that there is a strong relationship between the latent statuses and the items that are used to measure the latent statuses. Table 7 reports the δ parameters and τ parameters for 9th, 10th, and 11th grade are presented in Table 8.

Marijuana as a gateway for cocaine
(Model 2 vs. Model 1)

In order to address the question of whether marijuana is a gateway for cocaine, it is necessary to determine whether Model 2 fits the data better than Model 1. The AIC and BIC provide a way of making this determination. However, as Table 5 shows, in this case the AIC and BIC disagree. According to the BIC, Model 1 is a better fit than Model 2; the AIC suggests the opposite. In cases like this one where the evidence is mixed, it is customary to select the more parsimonious model (Collins, Graham, Long, & Hansen, 1994), which in this case is Model 1. Table 9 reports the ρ parameters. Table 10 reports the δ parameters, and the τ parameters for 9th, 10th and 11th grade are reported in Table 11.

Evidence for order of trying substances. If cocaine is frequently tried before marijuana, we would expect that the ADCcoc latent status would be sizeable. Table 10 shows that ACDcoc is nearly empty in the 9th (.000), 10th (.000), and 11th (.002) grade cohorts. This table also shows that the probability of being at the ACDMcoc stage is greater than the probability of being at ACDcoc stage for each of the three groups. For example, the proportion of 9th graders in the ACDMcoc latent status is .026 and the proportion of individuals in the ACDcoc status in .000. A substantially lower proportion of individuals in the ACDcoc stage when compared with the ACDMcoc stage is consistent with the idea that adolescents try marijuana before cocaine.

Evidence for increased risk. Table 11 shows that the probability of transitioning to ACDM conditional on membership on ACD at Time 1 (trying marijuana before cocaine) is greater than the probability of transitioning to ACDcoc conditional on membership on ACD (trying cocaine before marijuana) at Time 1. For instance, the probability of transitioning to ACDM conditional on membership on ACD at Time 1 for a 10th grader was .283; and the probability of transitioning directly to ACDcoc conditional on membership on ACD at Time 1

(trying cocaine before marijuana) was .000. These probabilities suggest that the risk of transitioning to trying cocaine increases after having tried marijuana.

Cigarettes as a gateway for drunkenness and marijuana
(Model 1 vs. Model 3)

Model 3 also appears to fit the data reasonably well. The G-square was 1950.129 with 12078 degrees of freedom. Both the BIC and AIC (Table 5) suggest that Model 3 should be selected over Model 1. Estimates for ρ, δ, and τ parameters are presented in Table 12-14, respectively.

Evidence for order of trying substances. Table 13 shows that the probabilities of getting drunk, using marijuana only or using marijuana and alcohol before using cigarettes (i.e. being at each one of the AD, M, and AM stages) are nearly zero. However, taken together, the sum of the probabilities of being at these stages (AD+M+AM) is approximately 2.2%-3.7% of the sample. This finding suggests that these stages might be necessary in the Substance Use Model and that there is a subgroup of adolescents that get drunk and try marijuana before trying cigarettes. Nevertheless, the probability of getting drunk and trying marijuana after having tried cigarettes is higher than the probability of getting drunk and trying marijuana before trying cigarettes (i.e. sum of the probabilities in AD + M+ AM). For instance, for 11th graders, the probability of experiencing drunkenness after having tried alcohol and cigarettes (ACD) is 9.0%; and the probability of experiencing marijuana after having tried alcohol and cigarettes (ACM) is 8.8%. These results suggest that most, but not all, adolescents try cigarettes before getting involved in drunkenness and marijuana.

Evidence for increased risk. Table 14 shows that the probability of getting drunk after having tried cigarettes (transitioning from AC to ACD) is greater than the probability of transitioning directly from alcohol to getting drunk without having tried cigarettes (transitioning from A to AD). For example, the probability of transitioning from AC to ACD is .145 for 11th graders, while the probability of transitioning from A to AD is .056. This table also shows that the probability of using marijuana after having tried cigarettes (transitioning from C to CM) is greater than the probability of using marijuana without having tried cigarettes (transitioning from No use to marijuana (M) or from Alcohol Only (A) to AM).

Discussion

In general, this study provides mixed evidence in support of the gateway hypothesis. The results of this study suggest that having tried marijuana precedes and increases the risk for trying cocaine. For example, the prevalence rate for trying cocaine without having tried marijuana was less than 0.2% for each cohort. The fact that ACDcoc (alcohol + cigarettes + drunkenness + cocaine) was nearly empty for the three cohorts also suggests that this stage might not be necessary in the Substance Use Model. In addition, the probability of using marijuana after having been drunk (ACD to ACDM) is greater than the probability of transitioning directly from drunkenness to cocaine without having tried marijuana (ACD to ACDcoc). This suggests that the risk of transitioning to trying cocaine increases after having tried marijuana. As a result, the hypothesis that marijuana is a gateway for cocaine met the two conditions of the Gateway Hypothesis, as discussed in Collins (2002).

However, the analyses suggest that trying cigarettes does not always precede or increase the risk for either trying marijuana or drunkenness. For instance, although probabilities of getting drunk, using only marijuana, or using marijuana and alcohol without having tried cigarettes (being at any one of the AD, M, and AM stages) are small, the sum of the

probabilities of *not* having tried cigarettes before trying marijuana or drunkenness were approximately 2% to 4% of the sample. This suggests that adolescents do *not* always try cigarettes before trying marijuana or experiencing drunkenness, indicating that cigarettes are not always a gateway for drunkenness and marijuana. One possible interpretation of these findings is that cigarettes are a gateway substance for one subset of individuals and not a gateway substance for another subset of individuals. It would be interesting to try to identify these subsets and then see if subset membership could be predicted using exogenous variables, such as gender, age, ethnicity, or parental tobacco use.

Prior research (e.g. Collins, Graham, Long, & Hansen, 1994; Collins, Graham, Rousculp, & Hansen, 1997; Collins, Hyatt & Graham, 2000; Graham, Collins, Wugalter, Chung, & Hansen, 1991; Hyatt Collins, & Graham, 2000; Kandel & Faust, 1975; Yamaguchi & Kandel, 1984a,b; Kandel, 1988; Kandel & Yamaguichi, 1993) has suggested that cigarettes play a more important role in the onset of substance use than has been supported by the present findings. One possible reason for the disparity is history. The AddHealth data set is fairly recent, and so these findings may reflect more current attitudes about tobacco use, or perhaps increased difficulty in obtaining cigarettes. Another possible explanation is that AddHealth was collected using very careful sampling procedures. Thus AddHealth may be more representative of the United States as a whole than most other data sets used in substance use research. However, in the present study we did not use the sampling weights that have been derived for the AddHealth data set. This limits the generalizability of the present findings. Another possible explanation for the disparity in results is that these studies did not examine their data using the criteria for meeting the Gateway Hypothesis outlined by Collins (2002). Of course, different scientific criteria can lead to different conclusions.

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Table 1: Manifest variables measuring the dynamic latent variable

Alcohol (A)	Have you had a drink of beer, wine, or liquor- not just a sip or taste of someone else's drink- more than 2 or 3 times in your life?
Cigarettes (C)	Have you tried cigarette smoking, even just one or two puffs?
Drunkenness (D)	Drink- Over the past 12 months, on how many days did you drink five or more drinks in a row?
	Drunk- Over the past 12 months, on how many days have you gotten drunk or "very, very high" on alcohol?
Marijuana (M)	How old were you when you tried marijuana for the first time?
Cocaine (coc)	Have you ever tried any kind of cocaine- including powder, freebase, or crack cocaine- for the first time?

Table 2: Restrictions on τ parameters for model 1

	No Use	A	C	AC	CM	ACD	ACM	ACDM	ACDM coc
No use	FR	FR	FR	FR	FR	FR	FR	FR	FR
A	0	FR	0	FR	0	FR	FR	FR	FR
C	0	0	FR	FR	FR	FR	FR	FR	FR
AC	0	0	0	FR	0	FR	FR	FR	FR
CM	0	0	0	0	FR	0	FR	FR	FR
ACD	0	0	0	FR	0	FR	0	FR	FR
ACM	0	0	0	0	0	0	FR	FR	FR
ACDM	0	0	0	0	0	0	FR	FR	FR
ACDMcoc	0	0	0	0	0	0	0	0	FR

* Table includes parameter restrictions for 9^{th}, 10^{th} and 11^{th} grade
FR = freely estimated 0 = fixed to 0

Table 3: Restrictions on τ parameters for model 2

	No Use	A	C	AC	CM	ACD	ACM	ACDM	ACDM coc	ACD coc
No use	FR	FR	FR	FR	FR	FR	FR	FR	FR	FR
A	0	FR	0	FR	0	FR	FR	FR	FR	FR
C	0	0	FR	FR	FR	FR	FR	FR	FR	FR
AC	0	0	0	FR	0	FR	FR	FR	FR	FR
CM	0	0	0	0	FR	0	FR	FR	FR	0
ACD	0	0	0	FR	0	FR	0	FR	FR	FR
ACM	0	0	0	0	0	0	FR	FR	FR	0
ACDM	0	0	0	0	0	0	FR	FR	FR	0
ACDMC	0	0	0	0	0	0	0	0	FR	0
ACDcoc	0	0	0	0	0	0	0	0	FR	FR

* Table include parameter restrictions for 9th, 10th and 11th grade
FR = freely estimated
0 = fixed to zero

Table 4: Restrictions on τ parameters for model 3

	No Use	A	C	AC	CM	ACD	ACM	ACDM	ACDM coc	AD	M	AM
No use	FR	FR	FR	FR	FR	FR	FR	FR	FR	FR	FR	FR
A	0	FR	0	FR	0	FR	FR	FR	FR	FR	0	FR
C	0	0	FR	FR	FR	FR	FR	FR	FR	0	0	0
AC	0	0	0	FR	0	FR	FR	FR	FR	0	0	0
CM	0	0	0	0	FR	0	FR	FR	FR	0	0	0
ACD	0	0	0	FR	0	FR	0	FR	FR	0	0	0
ACM	0	0	0	0	0	0	FR	FR	FR	0	0	0
ACDM	0	0	0	0	0	0	FR	FR	FR	0	0	0
ACDMcoc	0	0	0	0	0	0	0	0	FR	0	0	0
AD	0	FR	0	FR	0	FR	FR	FR	FR	FR	0	FR
M	0	0	0	0	FR	0	FR	FR	FR	0	FR	FR
AM	0	0	0	0	0	0	FR	FR	FR	FR	0	FR

* Table include parameter restrictions for 9^{th}, 10^{th} and 11^{th} grade
FR = freely estimated
0 = fixed to zero

Table 5: Comparison of the model fit indexes

	MODEL 1 Substance Use Onset model	**MODEL 2** Marijuana as a gateway for cocaine	**MODEL 3** Cigarettes as a gateway for drunkenness and marijuana
G^2	2995.592	2910.943	1950.129
Df	12150	12129	12078
Parameters estimated	137	158	209
BIC	4190.987	4289.573	3773.76
AIC	3269.592	3226.943	2368.129

Table 6: Estimates for the ρ parameters for response "yes" for model 1

	Ever tried alcohol	Ever tried cigarettes	Ever drink	Ever been drunk	Ever tried marijuana	Ever tried cocaine
No use	.000	.000	.007	.002	.006	.008
A	1.00	.000	.007	.002	.006	.008
C	.000	.930	.007	.002	.006	.008
AC	1.00	.930	.007	.002	.006	.008
CM	.000	.930	.007	.002	.997	.008
ACD	1.00	.930	.898	.923	.006	.008
ACM	1.00	.930	.007	.002	.997	.008
ACDM	1.00	.930	.898	.923	.997	.008
ACDMcoc	1.00	.930	.898	.921	.997	1.00

* Table include parameter estimates for 9^{th}, 10^{th} and 11^{th} grade

Table 7: Estimates for δ parameters for model 1

	9^{th}	10^{th}	11^{th}
No use	.275	.231	.207
A	.081	.084	.095
C	.134	.113	.093
AC	.189	.180	.147
CM	.035	.024	.026
ACD	.054	.079	.104
ACM	.085	.094	.098
ACDM	.120	.165	.195
ACDMcoc	.026	.031	.036

* Table include parameter estimates for 9^{th}, 10^{th} and 11^{th} grade

Table 8: Estimates of the τ parameters for model 1

9^{th} 10^{th} 11^{th}	No use	A	C	AC	CM	ACD	ACM	ACDM	ACDM coc
No use	.768 .790 .765	.113 .112 .121	.063 .021 .036	.013 .011 .026	.011 .006 .014	.004 .025 .035	.016 .017 .000	.011 .018 .003	.002 .000 .000
A	--	.887 .845 .841	--	.020 .012 .053	--	.052 .076 .046	.031 .016 .016	.003 .046 .044	.006 .005 .000
C	--	--	.603 .733 .661	.228 .189 .168	.023 .018 .036	.048 .028 .076	.052 .009 .000	.038 .017 .059	.008 .005 .000
AC	--	--	--	.656 .715 .714	--	.112 .118 .139	.096 .103 .072	.136 .054 .071	.001 .010 .003
CM	--	--	--	--	.462 .607 .672	--	.226 .219 .233	.205 .083 .072	.107 .091 .023
ACD	--	--	--	.383 .320 .263	--	.379 .395 .492	--	.214 .280 .232	.024 .006 .013
ACM	--	--	--	--	--	--	.723 .820 .622	.262 .139 .369	.015 .041 .009
ACDM	--	--	--	--	--	--	.303 .301 .222	.614 .666 .701	.082 .033 .007
ACDM coc	--	--	--	--	--	--	--	--	1.0

-- (fixed to 0)

Table 9: Estimates for the ρ parameters for response "yes" for model 2

	Ever tried alcohol	Ever tried cigarettes	Ever drink	Ever been drunk	Ever tried marijuana	Ever tried cocaine
No use	.000	.000	.007	.002	.006	.007
A	1.00	.000	.007	.002	.006	.007
C	.000	.931	.007	.002	.006	.007
AC	1.00	.931	.007	.002	.006	.007
CM	.000	.931	.007	.002	1.00	.007
ACD	1.00	.931	.896	.921	.006	.007
ACM	1.00	.931	.007	.002	1.00	.007
ACDM	1.00	.931	.896	.921	1.00	.007
ACDMcoc	1.00	.931	.896	.921	1.00	1.00
ACDcoc	1.00	.931	.896	.921	.006	1.00

* Table include parameter estimates for 9^{th}, 10^{th} and 11^{th} grade

Table 10: Estimates for δ parameters for model 2

	9^{th}	10^{th}	11^{th}
No use	.275	.231	.207
A	.081	.084	.095
C	.134	.113	.093
AC	.189	.180	.147
CM	.035	.024	.026
ACD	.055	.080	.103
ACM	.085	.093	.098
ACDM	.119	.164	.194
ACDMcoc	**.026**	**.030**	**.036**
ACDcoc	**.000**	**.000**	**.002**

* Table include parameter estimates for 9^{th}, 10^{th} and 11^{th} grade

Table 11: Estimates for τ parameters for model 2

9th 10th 11th	No use	A	C	AC	CM	ACD	ACM	ACDM	ACDM coc	ACD coc
No use	.768 .790 .765	.114 .112 .121	.064 .021 .036	.013 .011 .026	.011 .006 .013	.004 .025 .035	.015 .017 .000	.011 .018 .003	.002 .000 .000	.000 .000 .000
A	--	.886 .845 .841	--	.021 .012 .054	--	.052 .077 .046	.030 .016 .016	.004 .045 .043	.006 .005 .000	.000 .000 .000
C	--	--	.603 .733 .661	.228 .189 .167	.023 .018 .036	.048 .028 .076	.052 .009 .000	.038 .017 .059	.008 .005 .000	.000 .000 .000
AC	--	--	--	.655 .713 .714	--	.111 .115 .135	.097 .104 .074	.135 .054 .071	.001 .010 .003	.002 .004 .003
CM	--	--	--	--	.461 .606 .671	--	.223 .218 .233	.205 .084 .072	.111 .093 .024	--
ACD	--	--	--	.388 .320 .258	--	.349 .391 .490	--	**.222** **.283** **.238**	.022 .006 .014	**.020** **.000** **.000**
ACM	--	--	--	--	--	--	.724 .821 .622	.261 .139 .369	.015 .040 .009	--
ACDM	--	--	--	--	--	--	.296 .297 .219	.620 .669 .703	.084 .034 .078	--
ACDMC	--	--	--	--	--	--	--	--	1.00 1.00 1.00	--
ACDcoc	--	--	--	--	--	--	--	--	.000 1.0 .000	1.00 0.00 1.00

Table 12: Estimates for the ρ parameters for response "yes" for model 3

	Ever tried alcohol	Ever tried cigarettes	Ever Drink	Ever been drunk	Ever tried marijuana	Ever tried cocaine
No use	.000	.000	.004	.000	.000	.008
A	1.00	.000	.004	.000	.000	.008
C	.000	.976	.004	.000	.000	.008
AC	1.00	.976	.004	.000	.000	.008
CM	.000	.976	.004	.000	.997	.008
ACD	1.00	.976	.895	.916	.000	.008
ACM	1.00	.976	.004	.000	.997	.008
ACDM	1.00	.976	.895	.916	.997	.008
ACDMcoc	1.00	.976	.895	.916	.997	1.00
AD	1.00	.000	.895	.916	.000	.008
M	.000	.000	.004	.000	.997	.008
AM	1.00	.000	.004	.000	.997	.008

* Table include parameter estimates for 9^{th}, 10^{th} and 11^{th} grade

Table 13: Estimates for δ parameters for model 3

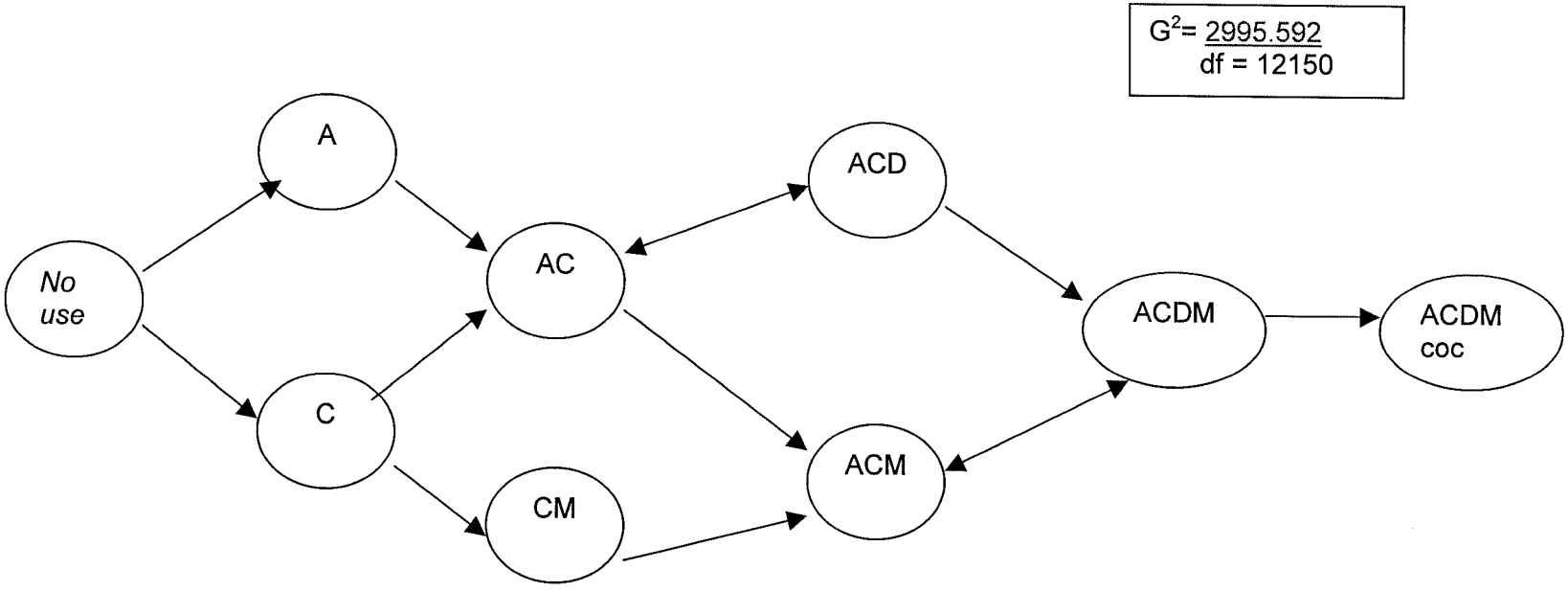
	9th	10th	11th
No use	.281	.235	.211
A	.088	.089	.098
C	.128	.108	.088
AC	.178	.171	.140
CM	.031	.018	.019
ACD	.048	.073	.090
ACM	.077	.083	.088
ACDM	.120	.164	.195
ACDMC	.026	.030	.036
AD	**.009**	**.010**	**.018**
MAR	**.005**	**.007**	**.008**
AM	**.008**	**.012**	**.011**

Table 14: Estimates for τ parameters for model 3

9th 10th 11th	No use	A	C	AC	CM	ACD	ACM	ACDM	ACDM coc	AD	M	AM
No use	.755 .766 .737	.101 .105 .110	.071 .034 .046	.017 .015 .028	.011 .005 .011	.002 .020 .021	.008 .017 .000	.011 .019 .005	.002 .000 .000	.009 .010 .018	.000 .010 .019	.013 .000 .005
A	--	.769 .727 .748	--	.085 .078 .102	--	.009 .015 .022	.028 .010 .010	.014 .049 .041	.006 .006 .000	**.060** **.079** **.056**	--	.029 .022
C	--	--	.600 .729 .657	.226 .187 .166	.026 .022 .040	.048 .028 .078	.053 .010 .000	.039 .017 .060	.008 .006 .000	--	--	--
AC	--	--	--	.651 .705 .704	--	**.118** **.125** **.145**	.096 .105 .074	.135 .055 .073	.000 .010 .003	--	--	--
CM	--	--	--	--	.452 .554 .659	--	.226 .209 .201	.222 .137 .105	.100 .099 .034	--	--	--
ACD	--	--	--	.352 .324 .264	--	.353 .375 .489	--	.268 .295 .243	.027 .006 .004	--	--	--
ACM	--	--	--	--	--	--	.713 .793 .616	.272 .161 .374	.015 .046 .010	--	--	--
ACDM	--	--	--	--	--	--	.305 .300 .220	.613 .667 .703	.082 .033 .077	--	--	--
ACDM Coc	--	--	--	--	--	--	--	--	1.0 1.0 1.0	--	--	--
AD	--	.410 .213 .301	--	.035 .070 .003	--	.202 .081 .019	.000 .080 .044	.000 .094 .167	.000 .038 .030	.237 .357 .402	--	.116 .067 .034

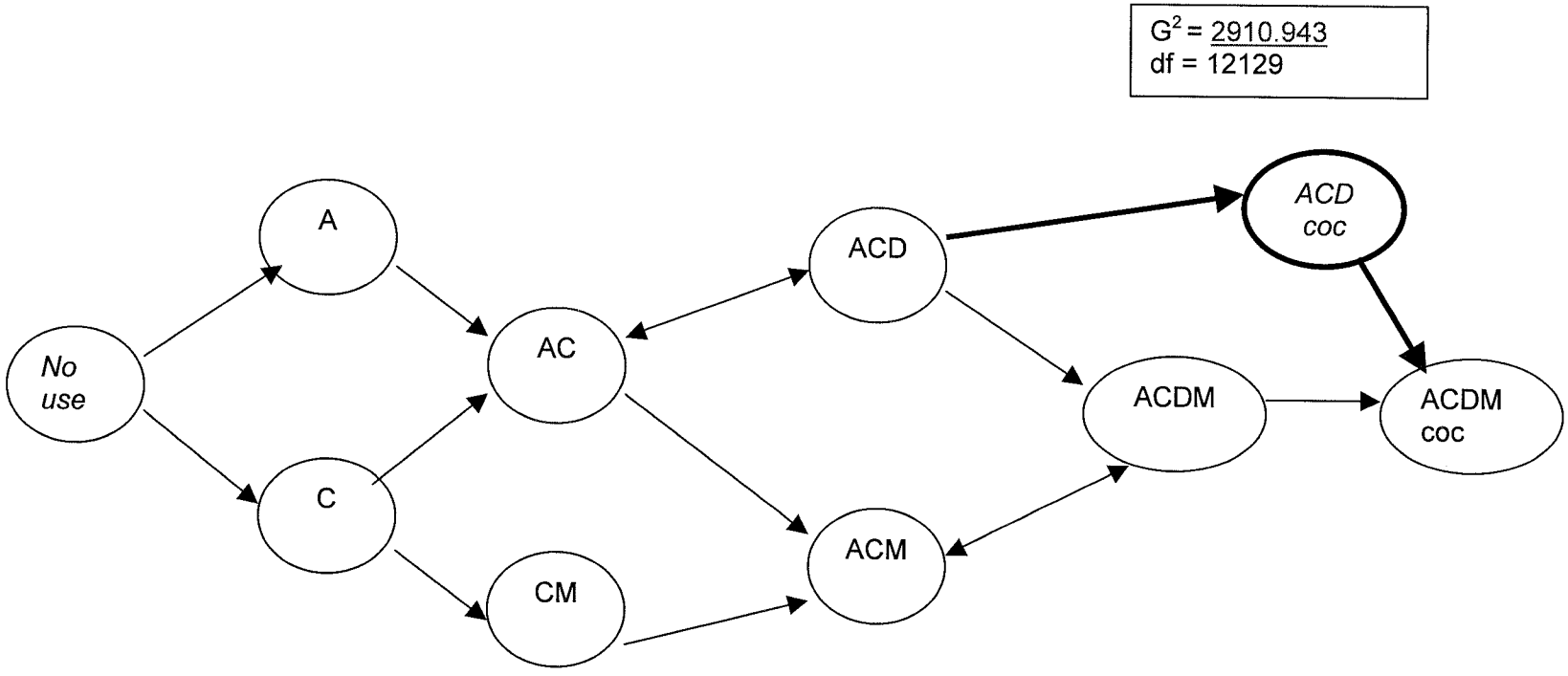
MAR	--	--	--	--	.000	--	.000	.091	.106	--	.566	.237
					.182		.130	.000	.068		.554	.066
					.000		.000	.000	.000		.714	.286
AM	--	--	--	--	--	--	.000	.217	.000	.000	--	.783
							.021	.012	.000	.000		.967
							.108	.324	.000	.000		.568

Model 1: Substance Use Model



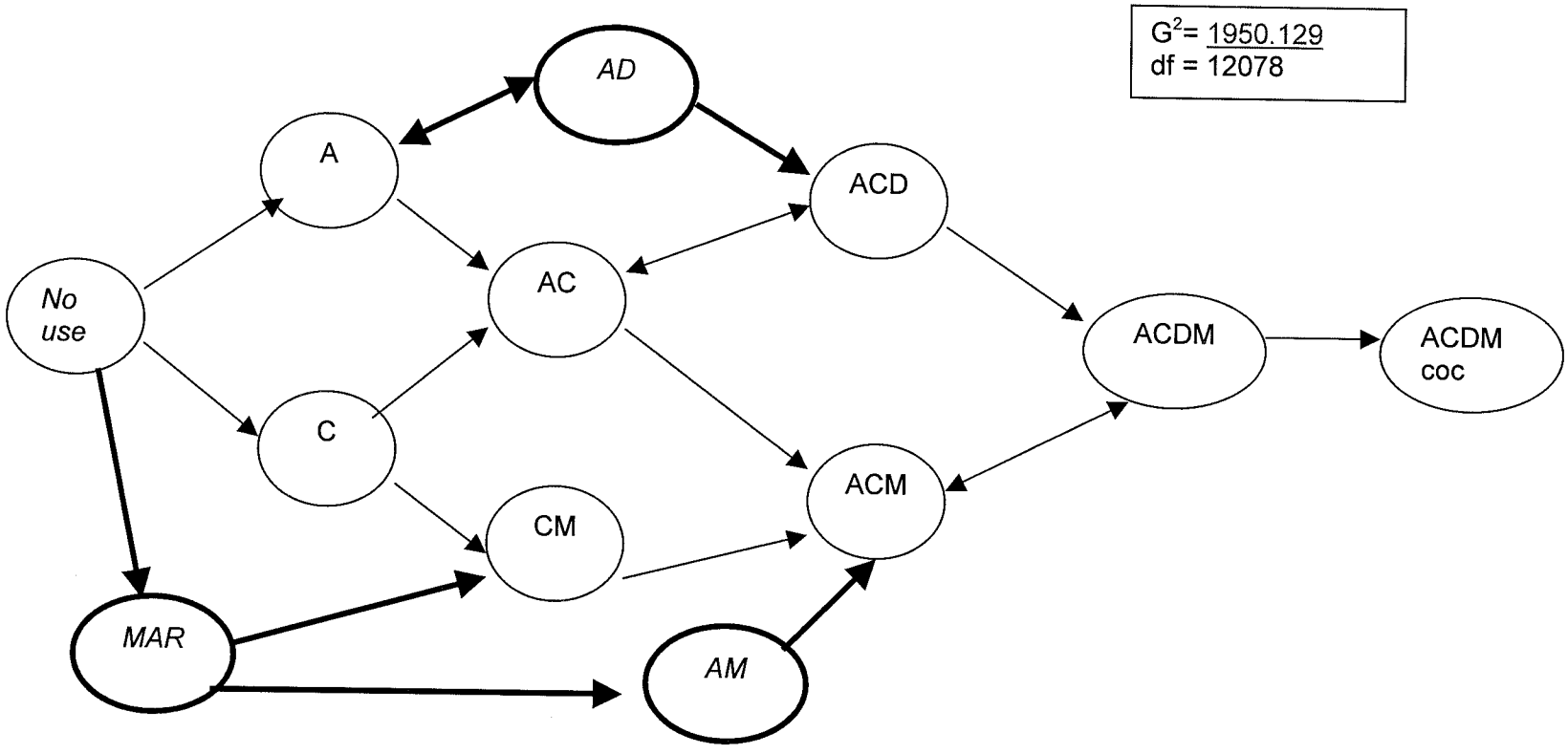
** This model was based on Hyatt & Collins (1999)

Model 2: Is marijuana a gateway for cocaine?



** If marijuana is not a gateway for cocaine then we would expect to need of the ACDcoc stage.

Model 3: Are cigarettes a gateway for drunkenness and marijuana?



** If cigarettes are not a gateway for drunkenness then we would expect to need of the AD stage.

** If cigarettes are not a gateway for marijuana then we would expect to need of the MAR and AM stages.