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A latent variable approach to measuring social dynamics in adolescence

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Abstract

In the study of adolescent health, it is useful to derive indices of social dynamics from sociometric data, and to use these indices as predictors of health risk behaviors. In this manuscript, we introduce a flexible latent variable model, as novel way of obtaining estimates of social integration and social status from school-based sociometric data. Such scores provide the flexibility of a regression-based approach while accounting for measurement error in sociometric indicators. We demonstrate the utility of these factor scores in testing complex hypotheses through a combination of structural equation modeling and survival models, showing that deviance mediates the relationship between social status and smoking onset hazard at the transition to high school.

Keywords

latent variables; measurement invariance; social networks

Numerous developmental theories emphasize that the peer context is integral to the emergence of health risk behaviors over time (Prinstein & Giletta, 2016). Fortunately, recent advances in social network methods allow researchers to empirically investigate the complexity of relations between features of the peer context and adolescent health risk behaviors (Veenstra, Dijkstra, Steglich, & Van Zalk, 2013). There are generally two approaches to using social network analysis to understand adolescent health risk behaviors. The first approach is what we refer to as a *direct* approach, which models the co-evolution of social networks and behaviors across multiple time points. This approach may be carried out using the stochastic actor-oriented modeling framework (SAOM; Snijders, 1996; Snijders, Van de Bunt, & Steglich, 2010), most often implemented using the SIENA program (Ripley, Snijders, Boda, Vörös, & Preciado, 2017), or through extensions of exponential random graph models (ERGM; Hanneke, Fu, & Xing, 2010; Krivitsky & Handcock, 2014; Robins, Pattison, Kalish, & Lusher, 2007). These models are well-suited to testing hypotheses about peer selection and influence on health risk behaviors because they directly take into account the time-specific set of connections between individuals in the network and allow these connections to be both predictors and outcomes of behaviors.

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The second approach, and the focus of this paper, is an *indirect* one,,whereby researchers first obtain person-level indicators from sociometric data and then use these indicators in subsequent statistical models to address questions about various relations between placement in the social network and behavior. This strategy has investigated the link between various dimensions of social standing and a wide variety of outcomes, ranging from depressive symptoms (e.g., Ueno, 2005) to peer aggression (e.g., Faris & Felmlee, 2011), to smoking e.g., (Lakon & Valente, 2012).

Each approach has benefits and drawbacks, but fundamentally they differ in the types of hypotheses that they are best able to evaluate. Direct approaches, such as the SAOM framework, represent the optimal way of understanding the relationship between connections within a given network and the spread of health risk behaviors over that network through peer selection and influence processes (Steglich, Snijders, and Pearson, 2007; Veenstra, Dijkstra, Steglich, & Van Zalk, 2013). By contrast, indirect approaches are not suited to testing peer selection and influence hypotheses at the network level, but are needed to test complex developmental hypotheses involving person-level indicators generated from social network analyses. As Prinstein and Giletta (2016) note, there are many processes in addition to selection and influence that may link peer network experiences to other predictors and to youth health risk behaviors. In particular, indirect approaches are needed for testing hypotheses about causal mechanisms involving developmental pathways spanning multiple domains in which social dynamics are simply one part of a person-level process. Such hypotheses may examine the role of social network variables in affective (Authors, in press) and family (Ennett et al., 2006) processes leading to substance use in adolescence. Thus, person-level social network measures may be useful pieces of flexible models for the development of health risk behaviors, spanning multiple domains.

However, there are significant methodological issues surrounding the measurement of these person-level sociometric indices. In the current paper, we examine two of these issues, measurement error and measurement invariance. We then introduce a latent variable model, the moderated nonlinear factor analysis (MNLFA; Bauer & Hussong, 2009; Curran et al., 2014), which may be used to address these issues. In particular, we discuss how MNLFA handles measurement error and resolves ambiguity regarding covariate effects in models using person-level sociometric indices. The flexibility of this approach – and its suitability for measuring social network constructs -- is explored through an empirical analysis of smoking onset around the high school transition, using longitudinal data from six school-based networks to obtain scores representing social status and social integration for each student, and using these scores to predict smoking onset in a mediation model. We focus the empirical example on substance use (smoking) because of extensive prior research in the contribution of social dynamics.

Measurement and social dynamics

Social functioning among peers is a critical aspect of many models concerning the development of substance use in adolescence (Prinstein & Giletta, 2016). Thus, indicators which summarize some aspect of an adolescent’s social functioning are frequently used in models to capture person-level risk for substance use. Adolescents’ self-reported social status (relative to peers) is linked to a variety of substance use behaviors, including smoking and drinking (e.g., Finkelstein, Kubzansky, & Goodman, 2006; Glendinning, Hendry, & Shucksmith, 1995). However, self-reported social status may be discrepant with the way in which adolescents are perceived by their peer network and reflect a variety of biases, as suggested by the relatively weak correlation between self- and peer-ratings of social status (Cillessen & Marks, 2011; Mayeux & Cillessen, 2008).

Sociometric data, in which peers provide information about others in their network, presents the opportunities for assessing social standing in the peer network (Cillessen & Marks, 2011; Prinstein & Giletta, 2016). This approach has been most often applied to classrooms of younger children. Key constructs assessed in these measures reflect social standing, often termed likeability or popularity. Likeability, which encompasses peers' acceptance of and preference for a given student (typically a classmate), is assessed by asking students to nominate the students they like the most or least (Parkhurst & Hopmeyer, 1998). From these ratings, researchers can calculate preference scores (e.g., the difference between the number of times an individual was nominated as liked vs. disliked) or create groupings based on different patterns of nominations (Coie, Dodge, & Copotelli, 1982). By contrast popularity, which reflects the reputation or prestige of a given student, may be assessed by asking students to nominate the most and least popular students in their network (LaFontana & Cillessen, 1999; Parkhurst & Hopmeyer, 1998; Cillessen & Bukowski, 2000). These sociometric indices have the advantage of capturing individual social functioning from peer nomination data, but they lack the ability to integrate information about more complex relationships in the larger social network (friends of friends). The approach also is not well suited to measuring adolescent peer relationships because their peer networks tend to be much larger school-based networks compared to the classroom-based network of younger children.

Advances in models for global social networks have allowed each adolescent's complex configuration of relationships to others to be distilled into a few person-level indicators of social standing. Network methods typically ask each student to nominate their best friends in the network, without the assumption that all students in the network know each other. Based on the collective pattern of relations among students in the network, indicators of a variety of measures of each student's position in the network can be discerned. Examples of network measures include counts of incoming and outgoing nominations (indegree and outdegree, respectively) and three-step reach centrality (which quantifies the proportion of the network an individual can reach in three friendship ties or fewer; see Table 1). Underlying the numerous social network measures are a smaller set of social network constructs, with the two most largely recognized being social status and social integration. Cillessen and Marks (2011) raise the point that these social networks measures index something fundamentally different from likeability or popularity, instead capturing the individual's connectedness within their network. To that point, Berkman et al. (2000) define social integration as an adolescent's embeddedness in a dense network of immediate connections, a social experience that may confer greater social support in the form of high-quality friendships. By contrast, social status reflects prestige and importance within the broader network (Berkman et al., 2000; Borgatti et al., 2009). Because measures of social status incorporate information about the adolescent's overall position within a network, higher social status may reflect an adolescent's ability to influence others and set trends. These constructs can be highly correlated with one another. However, as noted by Berkman and colleagues (2000) and Authors (under review), one can exist without the other. Adolescents may enjoy close friendships despite being of relatively low prestige in their overall network (i.e., high integration; low status), or be of great importance to their social network without being embedded in many high-quality relationships (i.e., high status; low integration).

Several studies show that social network measures are associated with substance use (Alexander, Piazza, Mekos, & Valente, 2001; Ali, Amialchuk, & Nikaj, 2014; Deutsch, Steinley, Sher, & Slutske, 2016; Ennett et al., 2006; Ennett et al., 2008; Lakon & Valente, 2012; Valente, Unger & Johnson, 2005); though a review of this literature reveals a complicated pattern of findings. Higher levels of measures such as indegree (the number of times an individual is nominated as a friend), betweenness centrality (a measure of an individual's tendency to connect other members of the network), and Bonacich centrality (a measure of an individual's connection to friends of high importance within the network), usually considered indicators of higher social status, have been linked to increased alcohol use (e.g., Ennett et al., 2006; Deutsch, Steinley, Sher, & Slutske, 2016) and smoking (e.g., Alexander, Piazza, Mekos, & Valente, 2001; Valente, Unger, & Johnson, 2005), though with variability by age and other contextual factors. Other studies have connected having relatively low personal network density (i.e., relatively few immediate friendship connections) and few reciprocated ties, which may signal low integration and potential social isolation within a network, to substance use (Ennett & Baumann, 1993; Tani, Chavez, & Deffenbacher, 2001; Ennett et al., 2006).

In reality, each social network measure reflects different aspects of an adolescent's social functioning imperfectly rather than any one aspect perfectly. By using each of these measures individually, researchers cannot account for the nuances in how each measure indexes some common aspect of social functioning. At the same time, however, combining these measures can be challenging given that they are often on different scales, and may have differentially strong relationships to the construct of interest. Here we adopt a psychometric approach, combining indicators and treating the common variance among them as reflective of a latent variable, namely social status or social integration. Though many different definitions of latent variables exist (Lord & Novick, 1968; Bollen, 2002; MacCallum & Austin, 2000), a latent variable can be generally defined as a construct that cannot be measured directly but which must be indexed by a set of observed indicators. A whole set of psychometric methods falling under the headings of factor analysis and item response theory (Joreskog, 1969; Lord & Novick, 1968) have been designed to address the issues arising from measuring latent variables with observed indicators, and we apply this framework here.

Applying a latent variable perspective carries two distinct advantages. First, by considering multiple indicators rather than any single one in isolation, we address the problem of measurement error. Friendship nominations may suffer from many of the measurement issues plaguing self-report indices – friendship ties may be spuriously added or omitted if a respondent intentionally names peers of perceived higher status, omits those of perceived lower status, or simply forgets to report names from all friends (Bernard et al., 1984;

Marsden, 1990). Measurement error in social network measures may also arise from common limitations due to study design, such as limiting the criteria for prospective adolescents' inclusion in the network (i.e., the boundary specification problem; Laumann, Marsden, & Prensky, 1989) or capping the number of nominations individuals can make. A growing body of research indicates that measurement error in social network studies may lead to inaccurate estimates of person-level sociometric indices (Borgatti et al., 2006; Costenbader & Valente, 2003; Kossinets, 2006; Smith & Moody, 2013; Smith, Moody, & Morgan, 2017; Wang, 2012), which would in turn lead to inaccurate estimates of the relationship between social standing and substance use.

Second, the use of latent variable models allows for a more precise understanding of interindividual differences in the relationship between social dynamics and substance use. This is particularly important due to the concern that the link between sociometric measures and substance may also not be constant across all adolescents or groups thereof. For instance, whereas most of the above-referenced studies find some link between social status and the use of tobacco, alcohol, or marijuana in school-based networks (Alexander, Piazza, Mekos, & Valente, 2001; Ali, Amialchuk, & Nikaj, 2014; Deutsch, Steinley, Sher, & Slutske, 2016; Ennett et al., 2006; Ennett et al., 2008; Lakon & Valente, 2012; Valente, Unger & Johnson, 2005), Barman-Adhikari and colleagues (2016) found no association between network centrality and methamphetamine use in networks of homeless adolescents. Moreover, in some cases the links between centrality and substance use appear to be stronger among white and male adolescents (Ali, Amialchuk, & Nikaj, 2014), a finding which has also been observed with respect to peer-nominated popularity and likeability (Choukas-Bradley, Giletta, Neblett, & Prinstein, 2015).

The crucial question in interpreting findings such as these is whether they reflect interindividual differences in the construct (e.g., social status or integration) measured by these indices, or in the measurement process itself. For instance, the finding that the link between Bonacich centrality and substance use is stronger among White adolescents than Black or Hispanic adolescents (Ali, Amialchuk, & Nikaj, 2014) may indicate that social status is a particularly strong determinant of substance use in these groups. Alternatively, it could simply reflect that Bonacich centrality is a differentially strong index of social status across groups, such that it measures something fundamentally different in White male adolescents than others. In the latent variable literature, these questions refer to the topic of measurement invariance (Byrne, Shavelson, & Muthen, 1989; Meredith, 1993; Millsap, 2012) or differential item functioning (DIF; Thissen, Steinberg, & Wainer, 1993; Osterlind & Everson, 2009). Under the assumption of measurement invariance, the relationship between an item (here, a person-level social network index) and the latent construct it is supposed to measure is identical across all individuals under study. In the presence of measurement invariance (i.e., in the absence of DIF), all variation in the observed variable can be attributed to the latent variable(s) it measures, rather than to background variables. If an index shows DIF on the basis of some covariate, however, that index does not necessarily mean the same thing across individuals.

We now introduce a model, the moderated nonlinear factor analysis model, which allows these two problems – measurement error and DIF – to be assessed and taken into account.

Moderated nonlinear factor analysis

An outgrowth of factor analysis and IRT (Joreskog, 1969; Lord & Novick, 1968), moderated nonlinear factor analysis (MNLFA) is a latent variable model which disentangles relationships between observed indicators, the latent construct they measure, and covariates (Bauer & Hussong, 2009; Curran et al., 2014). A schematic of an MNLFA (for modeling social integration from person-level indices) is shown in Figure 1. Mathematical expressions for the model are given in the Appendix. The MNLFA hypothesizes that the indicators (i.e., transitive triads, intransitive triads, reciprocity, out-of-school friends in Figure 1) all measure the same construct (i.e., social integration). These indicators are related to the latent variable through factor loadings (denoted by arrows between the latent variable and each indicator in Figure 1) which represent the predicted change in indicators associated with a one-unit shift in the latent variable. Additionally, each indicator is characterized by an intercept, which represents the predicted value of the indicator when the value of the latent variable is zero.

A unique feature of the MNLFA is that it allows covariates to explain observed differences in person-level indicators in two broad ways. First, the mean and variance of the latent variable may be affected by covariates, thus producing a corresponding change in the person-level index. Effects of covariates on the latent variable are referred to as impact. Suppose the measures in Figure 1 are used to measure social integration in an MNLFA. Suppose further that boys in a given network show lower overall outdegree than girls. This may be caused by mean impact, if boys are truly less socially integrated than girls in their peer networks; in this case the path from Male to the social integration latent variable (the MI path) would be negative.

Second, the parameters relating the indices to the latent variable may be affected by covariates. Effects of covariates on items, over and above the latent variable, are referred to as differential item functioning (DIF). Returning to the example of boys showing lower outdegree than girls in the model in Figure 1, intercept DIF would occur if boys simply nominated fewer of their peers as friends than girls did; in this case, the path from Male to outdegree (ID) would be negative. Similarly, if outdegree simply isn’t as strong an indicator of social integration for boys as it is for girls, this would manifest as loading DIF, and the path labeled LD would be negative.

Explicitly modeling impact and DIF allows substantively interesting effects of covariates on a construct of interest (i.e., impact) to be distinguished from effects of covariates on the items relating to some extraneous process outside of the latent variable (i.e., DIF). Numerous effects may occur at the person-level (e.g., gender, race, SES) and, given the presence of data from multiple networks, at the network level (e.g., network size; network density; clustering), where the ability to explicitly model this distinction may be particularly useful. For instance, consider the example of network size. Because several person-level social network indices increase or decrease with network size, many measures are normalized by dividing by network size. For example, this was how betweeness centrality was normed in this report. However, the relationships between some latent constructs and other person-level indices (e.g., outdegree and indegree, which may not increase deterministically with network size) may be affected by network size in ways that are more complex and difficult to model reliably.

Illustration of MNLFA in creating latent factors for social integration and status

We now demonstrate the use of MNLFA to assess the measurement of social status and integration by person-level social network indices. After assessing the measurement of these constructs using MNLFA, we generate scores which are used to examine the effects of social status and integration on smoking onset. Finally, we test the hypothesis that deviance mediates the effect of social status on smoking onset using a structural equation model.

Participants and Procedures.

Data come from the Context Study, which was designed to support investigation of individual and contextual factors (i.e., family, peer social network, school, and neighborhood contexts) that influence the development of substance use and other problem behavior from early to late adolescence. A full description of participants and study design is available elsewhere (Ennett et al., 2006; Authors, submitted), but are described briefly here. The study used a cohort-sequential design in which three cohorts of adolescents in the 6th, 7th, and 8th grades from three complete school districts in three primarily rural North Carolina counties were enrolled in the study and surveyed in school every six months for five data collection waves. Adolescents in two of the three school districts were surveyed in two additional waves, six and 12 months later. At wave 1, adolescents were enrolled in all 13 schools with middle grades (grades 6, 7, 8) in the three study school districts; three of these schools were alternative schools that included middle and high school grades. Beginning with wave 2, when the first adolescents transitioned to high schools, the school sample added all six high schools in the districts. The school sample size fluctuates across waves depending on the inclusion of middle and high schools and due to the single school system not participating at waves 6 and 7. The school-based design allowed measurement of peer social networks bounded by school enrollment and, during middle grades, by grade. Networks were defined on the basis of high school; as such, “school” here refers to the high school a student ultimately attends, even if the student wasis in middle school at a given time point. Thus, there were a total of six schools, denoted School A-School F. Sample sizes for each school were $N = 1677$ for School A, $N = 996$ for School B, $N = 493$ for School C, $N = 1642$ for School D, $N = 1015$ for School E, and $N = 1175$ for School F.

At each of the seven waves, adolescents completed a self-report battery which assessed mental health, peer and family relationships, and alcohol, tobacco and other substance use. Additionally, at each wave students completed a sociometric survey in which they were asked to nominate up to five of their closest friends, starting with their best friend. Nominations were made using a student directory, which contained an alphabetical listing of students and a unique four-digit identification code for each student. Out-of-school nominations could also be made using the identification number “0000.”

Survey Measures.

Demographic measures included adolescent-reported gender (effect-coded for analysis), race/ethnicity, child-reported parental education level, and grade (ranging over waves from Spring of Grade 6 to Grade 12). Though originally in ordinal scale, parental education was trichotomized to represent low (high school or less), medium (more than high school but less than a 4-year degree), and high levels of education (4-year degree or more), with medium used as the reference category. Additionally, due to low sample size of Hispanic/Latino students across schools, comparisons across race were limited to White and Black students, with White used as the reference category.

Smoking onset was measured at each wave with the item, "How much have you ever smoked in your life?" There were seven response options: "none at all, not even a puff" (0); "1 or 2 puffs, but not a whole cigarette" (1); "3 or more puffs but not a whole cigarette" (2); "1 to 2 whole cigarettes" (3); "3 to 5 whole cigarettes" (4); "6 to 20 whole cigarettes" (5); and "more than 20 whole cigarettes at once" (6). Onset as a binary variable representing any amount of smoking, which took a value of 1 if the subject had ever smoked at all -- i.e., if the subject gave a response above 0 on the original item -- and 0 otherwise.

Deviance was a factor score computed from 15 items, in five-point ordinal scale, from the Problem Behavior Frequency Scale (Farrell, Kung, White, & Valois, 2000). Each item assessed the frequency of a particular deviant behavior, such as skipping school, cheating on a test, or getting in a physical altercation over the past three months. Response options ranged from never (0) to ten or more times (4) in the past three months. The computation of deviance scores is described in greater detail by Authors (submitted).

Social network measures.

The above social network analysis resulted in a directed network, from which nine person-level social network indices were obtained using a combination of the UCINET program (Borgatti, Everett, & Freeman, 2002) and a set of SAS macros authored by James Moody (Moody, 2000). Person-level measures, listed in Table 1, were assumed to measure two separate but related latent constructs: social status and social integration. Measures of social status included betweenness centrality, Bonacich centrality, three-step reach, and indegree. Measures of social integration included transitive triads, intransitive triads, reciprocity, out-of-school friends (reverse scored so that more out-of-school friends represents lower social integration), and outdegree.

A plurality of these indicators are count variables (i.e., indegree; outdegree; reciprocity; out-of-school friends). We evaluated the density plots of each and because neither zero-inflation nor overdispersion were present, chose a Poisson distribution to model these person-level indices for all MNLFAs moving forward. The remaining indicators, including Bonacich centrality, three-step reach, betweenness centrality, transitive triads, and intransitive triads, were continuous, but the distributions of these variables varied widely from one school to the next. Because it was untenable to use different response distributions to model them across schools (e.g., a normal distribution in one school, and a highly skewed distribution such as a lognormal distribution in another), we chose to recode these indicators as categorical variables by binning data at percentiles (i.e., a median split for Bonacich and three-step reach centrality; at 33% and 66% for transitive triads, intransitive triads, and betweenness). This choice ensured comparability of the indicators across schools and allows us to reduce model complexity.

Generating social integration and social status scores using MNLFA.

MNLFA models were fit separately to six nonoverlapping samples corresponding to the six high schools to allow for relationships between the person-level indices, latent variables, and covariates to differ among the schools. The goal of the MNLFA fitting was to create factor scores indexing social status and social integration (see Table 1) that take into account impact and DIF due to the following covariates: gender, race, grade, network size, parental education, and cohort. We followed the sequence of steps described by Curran et al. (2014; 2017) for fitting an MNLFA and generating scores. Though a detailed description and rationale for these steps is provided elsewhere (Curran et al. 2014; Curran et al., 2017; Gottfredson et al., submitted), we give a general account of the procedure here[1].

First we established that social status and integration were each unidimensional by fitting a confirmatory factor analysis (CFA; Joreskog, 1969) Because the response distributions of the outcomes were parameterized using nonlinear link functions, the usual set of fit statistics (e.g., RMSEA, CFI) were not available. However, loadings were generally large (standardized loadings > .5) and significant, providing indirect evidence that social integration and status were well-measured by the factors. Given the complexity of fitting multivariate MNLFAs and our confidence that each construct was well-measured by its constituent indicators, we proceeded with fitting two univariate MNLFAs, one for social integration and one for social status. This step confirmed that outdegree, number of transitive triads, number of intransitive triads, reciprocity, and number of out-of-school friends were suitable measures of social integration; and that indegree, Bonacich centrality, three-step reach, and betweenness centrality were suitable measures of social status. Additionally, we conducted graphical analyses in which the relationship between each indicator and each covariate was visually examined. Visual inspection revealed differences in each of the items according to one or more covariates, indicating the potential presence of at least some covariate effects -- i.e., potential impact or DIF.

Following these exploratory steps, we drew a calibration sample consisting of one randomly-sampled observation for each individual. This was done to account for nesting of observations (i.e., multiple time points within a given person), as is standard in applications of IRT and MNLFA (Hambleton & Swaminathan, 2013; Bauer & Hussong, 2009). Parameter estimates were obtained (as described below) using this calibration sample, after which scores were generated for the entire sample.

We then sequentially tested for impact and DIF on the basis of covariates. That is, for each covariate effect, a model containing that covariate's impact on the mean of the latent

[1]This procedure is automated in a new R package, aMNLFA, which interfaces with Mplus to conduct all of these steps (Gottfredson, 2018). However, this package was not yet available at the time of the current analyses, and thus all analyses were conducted in SAS Version 9.3.

variable was fit, as were models testing each covariate's potential DIF effects on each item. In the current set of models, it was not hypothesized that either social integration or social status would show more variance according to any of the covariates; therefore, variance impact was omitted. A penultimate model containing all impact and DIF effects found to be significantly different from zero in these itemwise tests was then fit. Finally, nonsignificant effects were pruned using a Benjamini-Hochberg correction for multiple comparisons (Thissen, Steinberg, & Kuang, 2002).

The above yielded a total of twelve final models, one for social integration and social status within each of the six high schools. From each of these final models, modal a posteriori (MAP; Bock & Aitkin, 1981) scores for social integration and social status were obtained. Each MAP score represents an individual's estimated level of social status or social integration, which is then used as a predictor or outcome in subsequent models.

Results.

Descriptive statistics for factor scores within all schools are shown in Table 2. In all schools, as expected, there were strong positive correlations between each score and its constituent indicators; additionally, there were strong positive correlations between the two scores. Notably, the means of social integration and social status scores differed widely across the schools. This is likely due to the inclusion of different covariates in the models for each school's means. Thus, it was critical to include school as a fixed effect, as well as all covariates used in generating scores, in all subsequent analyses.

Table 3 summarizes all significant covariate effects found in the MNLFAs across all six schools. Importantly, DIF effects for social network size were necessary to include for a few indices including indegree, transitive triads, and intransitive triads, which are all directly proportional to network size. Thus, loading and intercept effects of network size were included on indegree in the social status model and for transitive and intransitive triads in the social integration model, regardless of whether item-wise tests were significantly different from zero. As shown, schools differed substantially in which covariates were linked to either differences in the factor means, or DIF in individual items. Among mean impact parameters, the most frequently observed effect was a negative effect of grade on both social integration (α = −0.1086, −0.0974, −0.1645 in Schools A, C, and F, respectively) and social status (α = −0.1073, −0.002, −0.1588 in Schools B, C, and E, respectively). Additionally, social integration was lower in subjects with lower levels of parental education in schools B, D, E, and F (where α = −0.200, −0.085, −0.094 −0.177 respectively), and social status was higher for Black students in schools B and E (where α = 0.063, 0.1368 respectively) and trivially lower in school D (where α = −0.004). This means, in general, that older students and students with lower parental levels of education were less socially integrated, and that younger students and Black students were of higher social status, within their networks.

DIF effects were less pervasive, but most frequently associated with gender and grade. In particular, in five of six schools, intercept DIF for reciprocity was found on the basis of gender, such that male subjects reported lower overall levels of reciprocity after controlling for social integration (ν = −0.081, −0.143, −0.134, −0.208, −0.9979 in Schools A, B, C, D, and F). This indicates that male students had fewer nominated friends reciprocate their nominations, even after controlling for social integration. DIF was also found for transitive and intransitive ties in the model for social integration, as well as Bonacich centrality, indegree, and three-step reach in the model for social status.

Illustration of using MNLFA scores for social integration and social status in analyses

After scores representing social integration and social status were generated, we used these scores as predictors in a series of models for smoking onset. In particular, we examined the temporal relationship between social integration, social status, deviance, and smoking onset.

Discrete-time hazard models of smoking onset.

The model for smoking onset during high school was a discrete-time survival model (Allison, 2014), which models the probability of a binary event taking place during some fixed number of time periods. Discrete-time survival analysis is described in greater detail elsewhere (see Allison, 2014; Singer & Willett, 1993; Willett & Singer, 1991). However, the two main functions under discussion are the hazard function, which represents the probability that a subject experiences smoking onset during a given time interval, and the survival function, which represents the probability that a subject has not experienced smoking onset by the end of a given time interval. The hazard of smoking onset was modeled as a function of several predictors. All covariates used in the estimation of the MNLFAs (race, gender, cohort, parental education, network size and school). Aside from network size, which is treated as time-varying, all predictors were included as time-invariant covariates. The predictors of interest here were social status, social integration, and deviance. Though they were available at all time points, the independent variables -- social integration, social status, and deviance -- were considered here as time-invariant predictors, owing to the difficulty of interpreting time-varying effects. Average values of social integration, social status, and deviance were computed across all time points and used as predictors here.

Finally, structural relationships between social status and deviance in the prediction of smoking hazard were examined using a discrete-time survival mediation model (DTSMM; Fairchild et al., 2015), a type of structural equation model which allows for a sequence of multiple temporally-ordered variables to predict a survival process. Whereas the regressions above may determine whether subjects' average levels of social integration, social status, and deviance predict greater smoking hazard overall, the DTSMM helps to determine the mechanism by which these variables affect one another and in turn lead to greater smoking hazard. The DTSMM is part of a growing set of models which treat the hazard of event occurrence as a latent variable in a structural equation model (Raykov et al., 2017; Muthen & Masyn, 2005). In the absence of structural relationships (e.g., a mediated path predicting survival), the DTSMM is identical to a typical discrete-time survival model. Preliminary analyses indicated that no mediated relationship existed between social integration and smoking onset. Therefore, we focus exclusively on social status here.

A key assumption of inferences based on the DTSMM is temporal precedence – that is, that the predictor precedes the mediator, which precedes the outcome (MacKinnon, Fairchild, and Fritz, 2007). Therefore, to include sequentially ordered predictors, mediators, and outcomes, we focused exclusively on a subset of cases and time points for these analyses. Hazard functions began at fall of 7th grade; predictors (social integration and status) were measured at spring of 6th grade; and the mediator (deviance) was measured at fall of 7th grade. Due to the cohort-sequential design of the study, only cases in one cohort (Cohort 1) were measured in spring of 6th grade, and these cases were only measured at seven time points: spring of 6th grade, fall of 7th grade, spring of 7th grade, fall of 8th grade, spring of 8th grade, fall of 9th grade, and fall of 10th grade. Thus, the sample was limited to Cohort 1 (N = 1236), and included only these seven time points.

Regression models.

Three discrete-time hazard regression models were fitted. First, a baseline model (Model 1) with no predictors determined the general pattern of smoking onset hazard across the study period. Second, a model with all demographic and methodological covariates (Model 2) tested whether smoking hazard was invariant across gender, race, parental education, cohort, school, and network size. Finally, models adding the effects of social integration, social status, and deviance factor scores as predictors were then fit (Model 3). Parameters from all discrete-time hazard models fit to the data are shown in Table 4.

Model 1 showed that the hazard of smoking onset started at $exp\left(\frac{1}{1+\exp(2.316)}\right) = .090.$ in fall of sixth grade and accelerated relatively quickly in middle school, with more than 50% of the sample initiating smoking before spring of 7th grade. Model 2, which added predictor effects from all covariates, showed that smoking onset probability was slightly higher among Black participants. Strong differences were observed with respect to parental education, with low parental education linked to higher risk for smoking and high parental education linked to lower risk for smoking relative to the medium-education group.

Model 3, which added factor scores for the mean levels of social integration, social status, and deviance, showed that, as expected, higher average levels of social integration were linked to lower hazard of smoking onset whereas higher levels of social status and deviance were linked to higher hazard of smoking onset. Model-predicted survival curves for subjects one standard deviation above and below the mean of social integration and status, holding all other predictors at sample averages, are shown in Figure 2. The probability of smoking onset increased rapidly during the middle school years for all subjects, but was lower overall for individuals of low social status or, to a lesser extent, high social integration.

Discrete-time survival mediation model.

Parameter estimates for the DTSMM are shown in Figure 3. Logit parameters of the baseline smoking onset hazard, shown in the rightmost portion of the figure, were comparable to their corresponding values in the discrete-time hazard models estimated for the larger sample. Among the covariates, only low parental education and attendance to School C significantly increased the hazard of smoking onset.

The primary goal of the DTSMM was to test whether social status in spring of 6th grade predicted deviance in fall of 7th grade, which in turn predicted greater smoking onset hazard – i.e., whether social status in spring of 6th grade exerted an indirect effect on smoking hazard, mediated by deviance in fall of 7th grade. However, to address the possibility of an alternate causal mechanism (i.e., deviance in spring of 6th grade predicting social status in fall of 7th grade, which predicts smoking onset), we included both social status and deviance at both time points. Deviance in the spring of 6th grade predicted higher deviance, but not higher social status, in the fall of 7th grade. In addition, social status in the spring of 6th grade predicted both higher social status and higher deviance in the fall of 7th grade. Additionally, deviance in the fall of 7th grade predicted smoking onset hazard, but social status in the fall of 7th grade did not.

Mediation analysis enables the magnitude of the total indirect path (the path through all mediators) and specific indirect paths (the path through any given mediator) from social status and deviance in fall of 6th grade to smoking onset hazard; corresponding standard errors are calculated using the delta method (Sobel, 1992). The hypothesized positive indirect effect of social status in spring of 6th grade on smoking onset hazard, transmitted through deviance in fall of 7th grade, was significantly different from zero (effect size =0.036, SE = 0.018, $p = .047$). Additionally, the indirect effect of deviance in spring of 6th grade on smoking onset hazard, transmitted through deviance in fall of 7th grade, was significantly different from zero (effect size =0.138, SE = 0.020, $p < .001$). Neither of the two possible indirect effects including social status in the fall of 7th grade was significantly different from zero. Thus, both deviance and social status in the spring of 6th grade were linked to higher levels of deviance in the fall of 7th grade, which increased the overall hazard of smoking onset.

Discussion

The purposes of the current analysis were twofold: first, to demonstrate the utility of an indirect approach to using an indirect approach to predicting health risk behaviors from an adolescent’s social network; and second, to introduce moderated nonlinear factor analysis (MNLFA; Bauer & Hussong, 2009; Curran et al., 2014), a flexible latent variable model, for the analysis of person-level indices arising from social network studies. The application of MNLFA to sociometric data is motivated by the need to achieve valid, reliable measurement of constructs such as social status and integration in adolescence. The method was used to obtain composite indices representing social status and social integration from longitudinal network data. When these indices were used as predictors of smoking onset hazard during the high school transition, social status was linked with a higher hazard of smoking and social integration with a lower hazard of smoking. Subsequent mediation analyses indicated that deviance in the fall of 7th grade mediated the effect of social status in 6th grade on later smoking hazard during the transition between middle and high school. These analyses demonstrated the capacity of MNLFA to obtain meaningful information about social functioning from social network data, advancing the applicability of psychometric methods to a uniquely rich source of data.

Our methodological aim in introducing and demonstrating MNLFA was to give researchers a tool for summarizing complex social dynamics, and placing these social dynamics within models for human growth and development. This widens the potential use of sociometric data to the testing of hypotheses in which social dynamics are a portion of a complex within-person process. This flexibility is necessary if researchers are to integrate sociometric data into the study of broader etiological models of health risk behaviors, which necessarily integrates information across contexts (e.g., biological, cognitive, and social) and time scales (e.g., moments, weeks, and semesters) to distinguish between normal and abnormal development (Cicchetti & Rogosch, 2002). Future work may focus on using MNLFA to pool network data across multiple different studies covering different but overlapping age ranges in the service of this goal, as has been its primary use with self-report data (Curran et al., 2014; Hussong, Curran, & Bauer, 2013).

MNLFA may also help to resolve some of the ambiguity in the relationship between social functioning and substance use. Studies using single indicators arising from social network data have found that measures of higher social status are generally associated with increased substance use (Abel, Plumridge, & Graham, 2002; Alexander, Piazza, Mekos, & Valente, 2001; Ennett et al., 2006; Ennett et al., 2008; Lakon & Valente, 2012; Valente, 2005). This conclusion is complicated by the concurrent finding that measures of social isolation are also associated with increased substance use, and that the links between these measures and substance use may not be uniform across subjects (Ennett & Bauman, 1993; Tani et al., 2001; Ennett et al., 2006). The current study demonstrated that MNLFA can be used to better understand what each of these indicators means, by quantifying their differentially strong relationships to social status and integration, as well as their differentially strong relationships to covariates such as sex, age, and race.

Although we believe that MNLFA is a useful addition to the arsenal of tools used to understand the role of the peer network in health risk behaviors, methodological advancements to the MNLFA framework are still needed. As noted by Steglich, Snijders, and Pearson (2010), the problem of network dependence (i.e., the fact that the network structure of the cases renders the assumption of independent residuals untenable) is incompletely addressed by most methods outside of models for network dynamics such as the SAOM (Snijders, 1996; Snijders, Van de Bunt, & Steglich, 2010). The MNLFA partially addresses network dependence indirectly by controlling for covariates, as residuals in the person-level indices will be independent to the extent that covariates such as gender, race, and age account for some of the dependence between observations. However, the problem of network dependence when using MNLFA scores should be investigated further in future work. Future work will focus on assessing the ability of MNLFA to rectify measurement issues in person-level social network indices through simulation studies. Our hope is that these assessments will further expand MNLFA's usefulness to the study of social dynamics in health and development.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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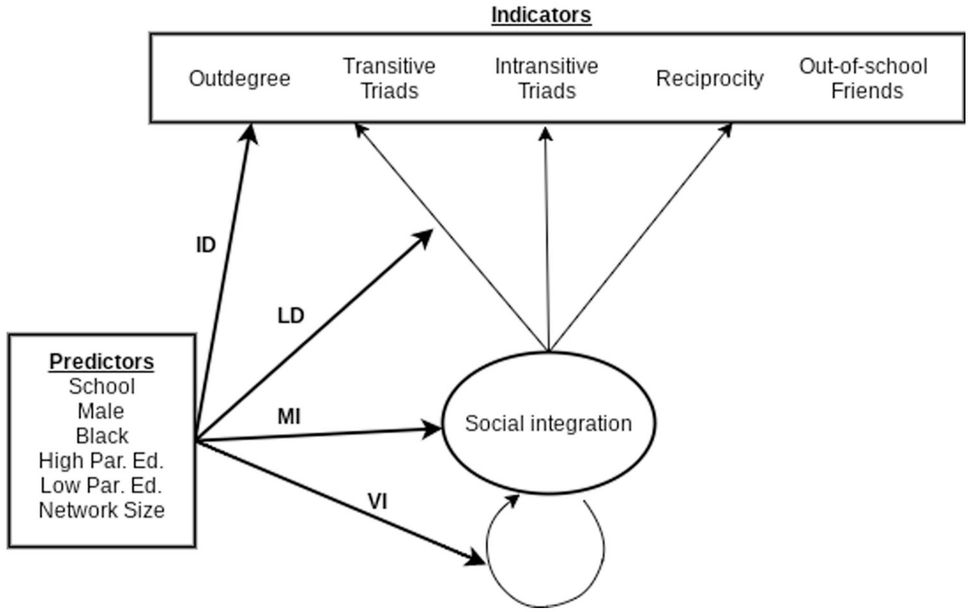

Figure 1.
Moderated nonlinear factor analysis with impact and DIF.

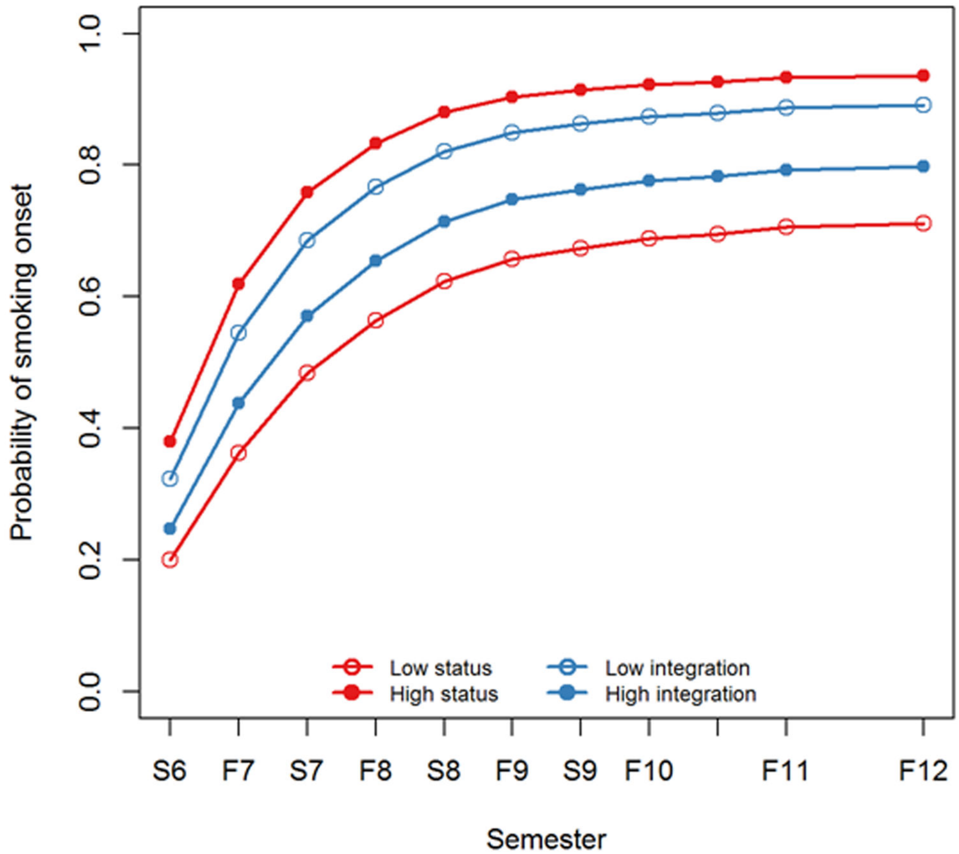

Figure 2.
Predicted inverse survival curves for subjects of high and low social integration and status.

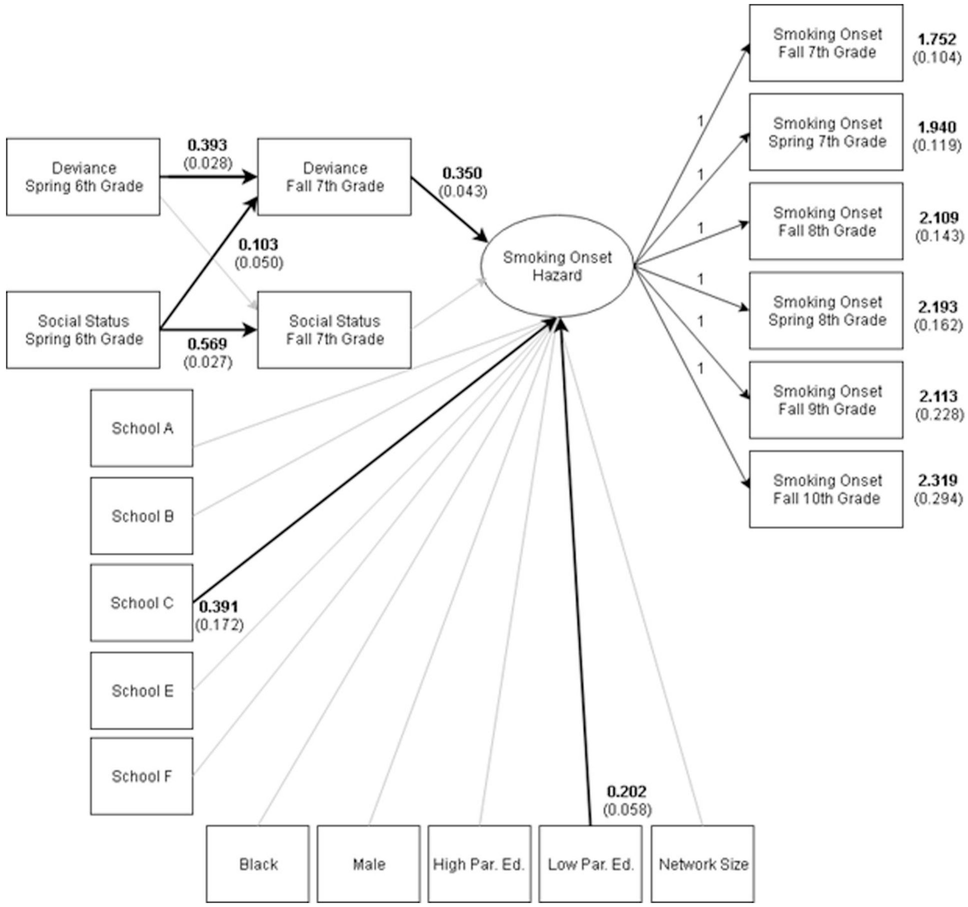

Figure 3.
Results from the discrete-time survival mediation model.

Table 1.

Summary of all node-level indices used in the analyses.

Node-level index	Factor measured	Definition
Indegree	Social status	Tendency to be popular: the number of in-school alters who nominate ego as friend (relative to the number of possible nominations).
Bonacich centrality	Social status	Tendency to have popular friends: the extent to which an adolescent has many friends who themselves have many friends.
Betweenness centrality	Social status	Tendency to connect adolescents who are not directly linked by a friendship tie: the proportion of all shortest social distance paths that include ego.
Three-step reach centrality	Social status	Tendency to be in close social distance to others: the proportion of the network that can reach ego in three ties or less.
Outdegree	Social integration	Tendency to choose friends: the number of in-school friendship nominations made by ego (up to 5).
Reciprocity	Social integration	Tendency to have reciprocated friendships: the number of ego's friendship nominations reciprocated by alter.
Transitive triads	Social integration	Tendency to be a friend of a friend's friend: the number of all triads containing ego where an alter's friend is a friend of ego.
Intransitive triads	Social integration	Conceptual complement to transitive triads: the number of all triads containing ego where an alter's friend is not a friend of ego.
Out of network friends	Social integration	Tendency to have friends not in the peer network: the number of nominations to friends not in the network.

Table 2.

Descriptive statistics of factor scores across schools.

	Social Status						Social Integration							
			Correlations with Indicators						Correlations with Indicators					
	Mean	**SD**	**Bonacich Centrality**	**Three-Step Reach**	**Indegree**	**Normed Betweenness**	**Mean**	**SD**	**Outdegree**	**Out-of-school friends**	**Reciprocity**	**Transitive Triads**	**Intransitive Triads**	***R*(Social Status, Social Integration)**
School A	0.066	0.824	0.563	0.710	0.781	0.644	0.024	0.734	0.483	0.415	0.601	0.489	0.804	0.650
School B	0.261	0.849	0.464	0.789	0.849	0.658	0.119	0.714	0.717	0.599	0.590	0.501	0.815	0.746
School C	−0.318	0.861	0.375	0.715	0.826	0.609	0.538	0.799	0.573	0.439	0.548	0.567	0.772	0.702
School D	0.017	0.818	0.375	0.697	0.837	0.595	0.029	0.738	0.613	0.486	0.641	0.479	0.798	0.751
School E	0.252	0.928	0.540	0.778	0.798	0.643	0.106	0.776	0.731	0.554	0.596	0.547	0.776	0.686
School F	−0.134	0.914	0.508	0.771	0.800	0.671	0.073	0.885	0.676	0.513	0.533	0.567	0.826	0.742

Table 3.

Abridged impact and DIF results for all MNLFA models fitted.

	Social Integration						Social Status				
		Item-specific DIF effects						Item-specific DIF effects			
Covariates	Mean impact	Outdegree	Out-of-school Friends	Reciprocity	Transitive Triads	Intransitive Triads	Mean impact	Bonacich Centrality	Three-step Reach	Indegree	Normed Betweenness
Main effects											
Black	C						BDE				
Cohort 1	AD										
Cohort 2	CD						CD				
Grade	ACF			E	A	E	BCE	B		A	
High Parental Education											
In High School							F				
Male	A			ABCDF	AC		EF		F		
Low Parental Education	BDEF						CF				
Network Size					*ABCDEF*	*ABCDEF*	C		D	*ABCDEF*	
Interactions											
Black*Grade							B				
Cohort 1*Grade											
Cohort 2*Grade											
High Parental Education*Grade											
Male*Grade					A		E				
Low Parental Education*Grade							BC				
Network Size*Grade	F				E					A	

Note. The letter codes used above are as follows. A = Effect found in School A; B = Effect found in School B; C = Effect found in School C; D = Effect found in School D; E = Effect found in School F; School E; F = Effect found in School F. Effects included as defaults (i.e., effects of network size on transitive ties, intransitive ties, and indegree) are shown in italics.

Table 4.

Parameter estimates from all discrete-time survival models.

	Model 1		Model 2		Model 3	
Model Fit						
Num.parameters	11		23		26	
Loglikelihood	−10176.790		−8164.790		−7758.55	
AIC	20375.580		16375.580		15569.100	
BIC	20449.857		16530.882		15744.639	
Model Parameters						
	β	SE(β)	β	SE(β)	β	SE(β)
Baseline Hazard Logit						
Spring 6th	−2.316**	0.053	0.121	0.095	−0.735**	0.105
Fall 7th	−2.527**	0.061	0.055	0.101	−0.713**	0.108
Spring 7th	−1.552**	0.041	−0.046	0.076	−0.798**	0.084
Fall 8th	−1.930**	0.053	−0.325**	0.084	−1.049**	0.091
Spring 8th	−1.012**	0.038	−0.485**	0.054	−1.184**	0.063
Fall 9th	−1.202**	0.051	−1.015**	0.079	−1.653**	0.084
Spring 9th	−1.929**	0.077	−1.771**	0.095	−2.383**	0.099
Fall 9th	−1.493**	0.078	−1.836**	0.11	−2.405**	0.112
Spring 10th	−2.351**	0.145	−2.603**	0.165	−3.138**	0.167
Fall 11th	−1.400**	0.13	−2.086**	0.163	−2.665**	0.164
Fall 12th	−1.544**	0.235	−2.644**	0.254	−3.206**	0.255
Predictor Effects						
Methodological Control Variables						
Cohort 1			−1.658**	0.076	−1.221**	0.078
Cohort 2			−0.916**	0.062	−0.685**	0.064
School A			−0.065	0.038	−0.113**	0.041
School B			−0.121**	0.048	−0.205**	0.052
School C			0.044	0.066	0.532**	0.077
School E			0.295**	0.048	−0.075	0.053
School F			0.219**	0.046	0.246**	0.048

Model 1	Model 2		Model 3	
Network Size	1.030**	0.085	0.982**	0.077
Demographic Control Variables				
Black	0.043	0.022	0.007	0.023
Male	0.028	0.019	0.000	0.02
High Parental Ed.	−0.079**	0.029	−0.213**	0.031
Low Parental Ed.	0.197**	0.021	0.24**	0.022
Social Dynamics and Deviance				
Deviance			0.508**	0.021
Social Status			0.516**	0.049
Indegree				
Normed Betweenness				
Bonacich Centrality				
Three-step In-Reach				
Social Integration			−0.240**	0.054
Outdegree				
Reciprocity				
Out-of-school Friends (reversed)				
Transitive Triads				
Intransitive Triads				