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Examining Proximity Exposure in a Social Network as a Mechanism Driving Peer Influence of Adolescent Smoking

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Abstract

Background: Adolescent peers' influence on tobacco smoking is a dynamic process affected by close friends and other network peers. Although research has examined the influence of immediate friends on smoking behavior (i.e., by cohesion exposure), the influence of all peers according to closeness (i.e., proximity exposure) remains unknown. This study introduces proximity exposure as a potential driver of peer influence.

Methods: Using the Teenage Friends and Lifestyle Study dataset, we examined 160 adolescents followed for 3 years and assessed their friendship ties and health behavior. Proximity exposure was calculated as the proportion of an individual's network peers who smoked, considering their distance from the individual. Path analysis was conducted with cross-lagged models testing the effect of proximity exposure on smoking frequency over time.

Results: Among nonsmokers without cohesion exposure (n=80), proximity exposure at year 1 was significantly associated with smoking initiation by year 3. Path analysis (n=160) indicated that smoking at year 1 predicted cohesion exposure by year 3. When proximity exposure was included, the effect of smoking on cohesion exposure was lost. Early smoking predicted future proximity exposure. However, the predictive value of early proximity toward future smoking was stronger.

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Contributors

Georges E. Khalil is responsible for the design of the study; Kayo Fujimoto and Eric Jones provided guidance on the design of the study; Georges E Khalil was responsible for the data analysis; Georges E Khalil, Kayo Fujimoto, and Eric Jones contributed to the conceptualization and design of the paper; Georges E Khalil drafted the paper; Kayo Fujimoto and Eric Jones critically revised the paper. All authors read and approved the final version. Georges E Khalil had full access to all of the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.

Author Credit Statement

Georges E. Khalil: Conceptualization; Data Curation; Formal Analysis; Writing-Original draft preparation; Writing-Reviewing and Editing.

Kayo Fujimoto and Eric Jones: Visualization; Investigation; Validation; Writing-Reviewing and Editing.

Conflict of Interest

All authors declare that they have no conflicts of interest.

Declaration of interests:

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Conclusion: These results suggest that proximity exposure can predict smoking even among nonsmokers without direct ties to friends who smoke. In support of a peer selection hypothesis, early smoking predicted friendship formation with smokers through cohesion. Conversely, in support of a peer influence hypothesis, proximity exposure predicted smoking. Researchers may consider developing interventions that decrease proximity exposure among adolescents.

Keywords

adolescent; smoking; tobacco; influence; selection; exposure; network

1. Introduction

1.1. Background

Adolescent smoking remains a major public health concern (Gentzke et al., 2019). Data from 42 countries across Europe and North America indicate that approximately 12% of 15-year-old adolescents smoke at least once per week (World Health Organization, 2016). Substance use behaviors such as tobacco smoking are typically initiated during adolescence (Gentzke et al., 2019), thus leading to early nicotine dependence (Coban et al., 2019), signs of pulmonary and cardiovascular diseases (Gold et al., 1996; Perrine et al., 2019), and carcinogenic processes at young age (Munshi, Heckman, & Darlow, 2015; Popa, 2012).

Among several factors, peer influence has been reported as a major predictor of adolescent smoking. Social network studies have shown that adolescents who occupy certain structural positions in a friendship network are more likely than others to initiate smoking (Montgomery et al., 2020). In particular, social influence has been identified according to (1) direct connection to smokers (cohesion) (Ennett et al., 2008; Wang, Hipp, Butts, & Lakon, 2018), (2) occupation of similar structural positions (structural equivalence) (Fujimoto & Valente, 2012), and (3) high nomination as a friend (popularity) (Mayeux, Sandstrom, & Cillessen, 2008). The factor most researched to date, cohesion (i.e., having friends who smoke) can predict smoking initiation (Alexander, Piazza, Mekos, & Valente, 2001; Bountress, Chassin, Presson, & Jackson, 2016; Ennett et al., 2008; Mercken, Steglich, Sinclair, Holliday, & Moore, 2012).

Although influence through cohesion occurs when adolescents conform to their friends' behaviors, proximate peers not nominated as friends may plausibly influence adolescents to smoke. Proximity is based on the number of steps it takes an adolescent to reach another person (e.g., friends of friends versus friends of friends of friends) (Koutra & Faloutsos, 2017). However, studies have rarely examined the structural property of network proximity to conceptualize this influence. The current study aimed to examine peer influence in terms of network proximity by considering individuals' structural closeness to smokers.

1.2. Theoretical Framework

Differential association theory (Cressey, 1978) and social learning theory (Bandura, 1977) have dominated research on peer influence and substance use. According to differential association theory, adolescents learn to engage in behaviors by interacting with friends. Research on cohesion has indicated that adolescents learn their friends' attitudes and behaviors through direct contact (Fujimoto & Valente, 2012; Valente, Gallaher, & Mouttapa, 2004). Alternatively, social learning theory suggests that adolescents may learn from observing and modeling others who engage in behaviors, without necessarily interacting with them or befriending them. Although both models support direct exposure to peers, social learning theory does not necessarily require direct interaction with others. Consequently, proximity to smokers who are not necessarily friends may facilitate influence.

1.3. Proximity Exposure as a Mechanism of Influence

A review of the most recent research has found that a direct connection to others cannot sufficiently explain the influence or diffusion of behavior in a network (Montgomery et al., 2020). Instead, during their continued development, adolescents face fewer environmental and parental constraints, join new social circles, and become exposed to peer-behavior beyond that of their friends (Bajaj & Nancy, 2019; Ennett et al., 2008).

Network research has also indicated that adolescents may be influenced by proximate peers, given that they encounter these peers in social situations, without befriending them, and still be exposed to their behaviors (Behler, 2017). Adolescents may be exposed to classmates in a school grade, or teammates through co-participation in extracurricular activities, and model their behaviors in absence of friendship (Fujimoto, Wang, & Valente, 2013). In a friendship network, two individuals interconnected only through their peers may still be exposed to each other's behaviors (Burt, 2010). For instance, influence based on structural equivalence (i.e., when two individuals have connections with the same peers) can be a stronger predictor of smoking behavior than is influence based on cohesion (Fujimoto & Valente, 2012).

We conceptualize individuals' proximity exposure as an individual's level of exposure to all smokers in a network. This exposure is determined based on the shortest distance between the individual and the smokers in the network. One investigation of proximity exposure, conducted by Payne and Cornwell (2007), has examined path distances by measuring social influence on risk-taking at two steps (i.e., friends of friends) or three steps (i.e., friends of friends of friends) from an adolescent. Both close friends and indirect connections to peers have been found to be influential. However, because exposure increases with decreasing path distance, Fujimoto and Valente (2012) have reported that the influence is stronger when two adolescents are fewer steps from each other. Thus, a proximity approach can capture direct and indirect exposures. However, these studies have not considered the distance to all other adolescents in the network. Although they have not presented a concrete measure of proximity exposure, they have indicated the need for such a measure. Figure 1 depicts this overlap between cohesion and proximity.

1.4. Smoking Behavior Predicting Network Positions

Adolescents' smoking behavior may determine their popularity, tendency to make friends who also smoke, and tendency to become closer in the network to other smokers. First, depending on school culture or the smoking norms in which adolescent networks are embedded, smoking may aid or hinder adolescents in building friendships, ultimately affecting their popularity (Mayeux et al., 2008; Michell, 1997). Second, on the basis of behavioral homophily, adolescent smokers tend to select friends who also smoke. This process of friendship selection is an established phenomenon in the context of adolescent smoking (Hoffman, Monge, Chou, & Valente, 2007; Mercken et al., 2012). In some cases, peer selection based on similar smoking behavior has been found to be more likely to occur than peer influence from friends who smoke (Mercken et al., 2012). Third, in a situation similar to cohesion, adolescents who smoke can work to become closer in the network to others who also smoke, ultimately increasing proximity exposure. For example, they can select the friends of their friends based on their similarities (Burk, Steglich, & Snijders, 2007).

1.5. Study Objective

We first examine peer influence mechanisms of cohesion and proximity exposure as predictors of smoking initiation. We then investigated which mechanism is a stronger predictor of smoking—while considering the potential effect of smoking on network positions. The tested associations are summarized in Table 1.

2. Data and Methods

2.1. Study Design

We retrospectively analyzed data collected during the Teenage Friends and Lifestyle Study (Pearson & West, 2003), focusing on smoking initiation during early-to-mid-adolescence and the transition from experimental to regular smoking. In this longitudinal study, 160 adolescents in Glasgow (United Kingdom) were followed from their second to fourth year in one secondary school (3-year follow up).

2.2. Measures

2.2.1. Smoking Frequency and Initiation—For smoking frequency, adolescents reported whether they were nonsmokers (never smoked in their lifetime), occasional smokers (<1/week), or regular smokers (>1/week). By examining the distribution within categories, smoking status was dichotomized as never-smokers or smokers (occasional or regular) (Lejuez et al., 2005). Nonsmokers' initiation is measured using their smoking status at year 3.

2.2.2. Friendships—Participants were asked to nominate up to six friends. For each, they indicated whether this person was "a best friend" (coded 2), or "just a friend" (coded 1). Individuals not nominated were coded 0.

2.2.3. Measures of Network Influence—Network measures included popularity, cohesion exposure (E_C) and proximity exposure (E_P). We measured adolescents' popularity by using in-degree centrality (i.e., the frequency of being selected as a friend) (Koutra & Faloutsos, 2017) instead of likability (Mayeux et al., 2008). For distribution adjustment, popularity was computed as the log of the in-degree centrality (Fujimoto & Valente, 2012). To compute E_C and E_P, we used the network exposure model described by Valente (2005). E_C, the degree to which an adolescent was exposed to direct friends who smoke, was calculated by multiplying the adjacency matrix of a friendship network (W) by the nominated friends' smoking status (coded as 1 or 0).

To compute E_P (Appendix A), we first extracted a matrix of geodesic distance, which is the shortest path between each pair of adolescents (Koutra & Faloutsos, 2017). Whereas previous research has examined proximity at a maximum of three steps (Payne & Cornwell, 2007), we considered proximity by examining friendship ties up to the highest number of geodesic steps in the network. We converted the matrix of geodesic distance into a matrix of closeness or proximity, by subtracting the distance between two adolescents from the maximum obtained distance in the network plus one (similar to the one proposed by Valente and Foreman's (1998) measure radiality). Cohesion and proximity were reported as percentage scores, which accounted for differences in the number of nominated friends.

There are clear situations in which influences of cohesion and closeness overlap, because cohesion entails the closest connection between two adolescents (i.e., a direct connection). Although recoding E_P may disentangle the two measures of influence, we chose to acknowledge that cohesion is by definition a form of proximity. Consequently, we accounted for the overlap between measures as part of our statistical analysis (as described below). In particular, E_P measures the extent to which adolescents are exposed to a behavior through all network members, including direct friends and non-adjacent proximate peers.

2.2.4. Other Variables—

Socio-demographic variables included age (in years), gender (being female), and socio-economic status, measured as the amount of pocket money that adolescents received from their parents per month (Furnham & Milner, 2017).

2.3. Data Analysis

First, with t-test and Chi-square statistics, we compared years 1 and 3 with respect to network characteristics. To examine the role of cohesion exposure and proximity exposure separately as predictors of smoking initiation, we estimated three logistic regression models with adolescent nonsmokers at year 1. For the first two models, we checked whether cohesion exposure at year 1 (Model 1) and proximity exposure at year 1 (Model 2) predicted smoking initiation at year 3. The third model involved proximity exposure predicting smoking at year 3 among nonsmokers who scored zero on cohesion exposure. Logistic models controlled for gender, age, and having smokers in the household.

With path analysis, we investigated which mechanism is a stronger predictor of smoking frequency. For all participants, we conducted two cross-lagged linear path models to allow for reciprocal associations, estimating a two-time-points, three-variable panel model and a two-time-point, four-variable panel model (Figure 2; Newsom, 2015). We adjusted for age, gender, presence of smokers in the household, and socio-economic status. The main variables at years 1 and 3 were smoking frequency, cohesion exposure, proximity exposure (only in the second model), and popularity.

Path analysis allowed us to estimate cross-lagged models combining test-retest, synchronous, and cross-lagged correlations (Newsom, 2015). These models effectively highlighted the direction of the relationship between peer-exposure and smoking, thereby accounting for the dilemma between peer influence (i.e., peer relationships cause smoking) and peer selection (i.e., smoking causes selection of peer relationships). In addition, path analysis controlled for the expected correlation between cohesion exposure and proximity exposure. The path model fit criteria included: (1) a nonsignificant chi-square goodness-of-fit, (2) a comparative fit index (CFI) of 0.90 or greater, (3) a root mean square error of approximation (RMSEA) less than or equal to 0.06, and (4) a standardized root mean square residual (SRMR) lower than 0.08 (Hooper, Coughlan, & Mullen, 2008). To estimate the importance of accounting for proximity exposure, we compared the model in Figure 2 with a model lacking associations between proximity exposure and other network variables of interest (Appendix B), with respect to the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). These statistics are used when comparing nested models estimated with the same data and indices to test which model is most parsimonious (Kwok, Cheung, Jak, Ryu, & Wu, 2018). Smaller values suggest better fit. We performed a likelihood ratio test (LRT) to capture the chi-square difference between these models. We also used LRT to compare the model in Figure 2 with one that imposes constraints on cross-lags (paths linking proximity exposure and smoking at years 1 and 3). Centrality and exposure measures were calculated using UCINet version 6, and statistical analyses were performed using STATA version 14.

3. Results

3.1. Socio-demographics and Network Characteristics:

Table 2 reports sociodemographic and network characteristics for the sample (N = 160). From year 1 to year 3, this cohort exhibited an increase in the percentage of smokers ($p < 0.001$), cohesion exposure ($p < 0.001$), and proximity exposure ($p < 0.001$). Popularity measured by in-degree centrality (the proportion of being nominated as a friend) decreased from year 1 to year 3 ($p = 0.001$). Cohesion and proximity exposures were moderately related ($R = 0.44$, $p < 0.001$). There was no relationship between popularity and either of the exposure measures.

3.2. Predicting Smoking Initiation among Nonsmokers:

The first logistic model indicated that nonsmokers with higher cohesion exposure were more likely to initiate smoking by year 3, OR = 1.03, $p = 0.006$. The second model showed that nonsmokers with higher proximity exposure were more likely to initiate smoking by year 3, OR = 1.37, $p < 0.001$. A third model with nonsmokers who lack cohesion exposure at year 1 ($n = 80$) showed that higher proximity exposure was still associated with smoking initiation by year 3, OR = 1.36, $p = 0.023$. Appendix C presents all three models.

3.3. A Cross-lagged Model Lacking Proximity Exposure Predicting Smoking:

An initial cross-lagged model lacking proximity exposure (Figure 3) indicated that smoking at year 1 predicted cohesion exposure by year 3, β (SE = 0.08) = 0.19, $p = 0.015$. However, early cohesion exposure did not predict future smoking, β (SE = 0.09) = 0.10, $p = 0.229$. The model showed good fit ($\chi^2_{11} = 8.32$, $p = 0.685$, CFI = 1.00, RMSEA < 0.001, 90% CI 0.00 – 0.077, SRMR = 0.03).

3.4. A Cross-lagged Model with Proximity Exposure Predicting Smoking:

When we used a similar model including proximity exposure (Figure 4), some paths lost significance. Smoking at year 1 did not predict later cohesion exposure, β (0.08) = 0.05, p =

0.470, and cohesion exposure at year 1 did not predict later smoking, β (0.09) = −0.002, p = 0.978. However, there was a significant relationship between proximity exposure at year 1 and smoking by year 3, β (0.10) = 0.25, p = 0.010. Smoking at year 1 also predicted proximity exposure by year 3, but with smaller effects, β (0.05) = 0.11, p = 0.025. LRT indicated a significant chi-square difference between this model and one imposing constraints on these paths (LRT $\chi^2(1) = 4.11$, $p < 0.05$). In addition, early smoking predicted lower popularity by year 3, β (0.08) = −0.22, p = 0.008. However, popularity at year 1 did not predict smoking by year 3, β (0.07) = 0.04, p = 0.558.

Overall, this model indicated good fit ($\chi^2_{15} = 12.34$, p = 0.653, CFI = 1.00, RMSEA < 0.001, 90% CI 0.00 – 0.07, SRMR = 0.04). When paths were omitted between proximity exposure and all the variables "smoking frequency", "cohesion exposure", or "popularity", the new model a poorer fit ($\chi^2_{25} = 125.13$, $p < 0.001$, CFI = 0.78, RMSEA = 0.19, 90% CI 0.15 – 0.22, SRMR = 0.14). The LRT indicated a significant chi-square difference between models (LRT $\chi^2(10) = 112.78$, $p < 0.001$). With the omitted relationships, AIC increased from 5203.41 to 5296.19 and BIC increased from 5409.93 to 5475.18. Appendix D presents the two models.

4. Discussion

Previous research has concluded that cohesion exposure and popularity play primary roles in driving peer influence to smoke (Montgomery et al., 2020). The present study expanded on this research by investigating peer influence on the basis of proximity exposure to smokers. Our results mainly indicated that (1) proximity exposure predicted smoking, even in the absence of cohesion exposure, and (2) based on proximity exposure, peer influence was more powerful than peer selection.

While cohesion exposure is limited to the frequency of friends who smoke, proximity exposure relates to the exposure to smokers at the broader level of a peer network. Our findings support that this type of exposure can explain peer influence at the macro-level in a sociological system. Proximity correlated with cohesion because proximity exposure includes cohesion exposure. Separately, both exposure measures predicted smoking initiation among nonsmokers. However, extending the findings of Payne and Cornwell (2007), we found that nonsmokers with an initial lack of cohesion exposure still initiated smoking as a result of proximity exposure. Proximity exposure is thus a powerful indicator of peer influence, and even when cohesion exposure is not detected, researchers may still predict smoking by considering proximity exposure.

Our first path model indicated that friendship selection based on smoking was a stronger process than smoking based on friendship. While controlling for the effect of early cohesion exposure on future smoking, we found that adolescents' early smoking at year 1 significantly predicted the formation of more relationships with friends who smoke by year 3. This finding indicates that friendship selection may be a more robust predictor of network dynamics than friendship influence (as supported by LRT analysis; Mercken et al., 2012). This result is in line with differential association theory, which holds that a direct interaction between friends is responsible for reinforcing risky behaviors.

In a second path model, proximity exposure predicted future smoking, suggesting peer influence by proximity. In addition, early smoking predicted future proximity exposure, suggesting peer selection by proximity. Beyond selectng friends who smoke (Steglich, Snijders, & Pearson, 2010), smokers may work to become closer in distance to other smokers. This proximity allows them access to cigarettes and smoking cliques that reduce stigma and promote affinity (Hsieh & VanKippersluis, 2018). However, based on our LRT findings, peer selection by proximity was found to be weaker than peer influence by proximity. This finding may be because proximity exposure relies on connections that are beyond direct ties. Clearly, both peer selection and peer influence are at work. In support of the social learning theory, proximity to smokers who are not friends may present norms that facilitate smoking behavior, influence, and reaching out to other smokers (Simmons-Morton & Farhat, 2010). Consequently, whereas proximity exposure predicts smoking initiation, cohesion exposure may be responsible for driving smoking maintenance. In addition, relationships between proximity exposure and other variables in the model contributed to a better overall fit of the model. This result suggests that accounting for proximity exposure is key when predicting influence and selection. Uniquely to this study, the results indicated a negative association between smoking and popularity, possibly because of school social norms. By measuring popularity on the basis of likability, Mayeux and Colleagues (2008) have found that when school norms are against smoking, adolescents may begin to lose popularity because of their smoking behavior.

Of note, proximity exposure involves two dimensions: (1) the proportion of smokers in the network and (2) their distance from the ego. Consequently, a high proximity exposure score may be due to a large proportion of smokers in the network, a short distance to smokers, or both. The difficulty in disentangling these two dimensions may create a challenge in identifying the dimension responsible for our measure’s success. Nevertheless, having the two dimensions in one measure explains the strength of proximity exposure as a mechanism of peer influence.

In the context of social networks, regression models have limitations in estimating network effects, even with path analysis because they cannot completely account for interdependencies that arise from the extension of social ties and their change over time. Future research should include exponential random graph modeling to account for changes in certain structural properties. Nevertheless, path analysis with a cross-lagged design allowed us to (1) follow adolescents over time, (2) account for inter-correlations between exposure measures and smoking, and (3) disentangle peer influence from peer selection. The analysis also allowed us to include both cohesion exposure and proximity exposure in a system of equations.

Individuals not connected to each other may still have similar connections to others. Future research testing proximity exposure may consider accounting for peer influence mechanisms that are unrelated to peer connections (e.g., structural equivalence). Structural equivalence can be a stronger predictor of smoking than is cohesion exposure (Fujimoto & Valente, 2012). Adolescents tend to affiliate with others who are demographically similar to them (Dijkstra, Cillessen, & Borch, 2013), and future analysis could account for friendship selection based on sociodemographic similarities. In addition, factors that were not considered (e.g., media exposure, sensation-seeking, and access to tobacco) may have affected the study findings. In future research, proximity exposure could be examined from the perspective of traffic flow of information and behavior contagion. This analysis could be accomplished through entropy centrality, assuming that behaviors can transfer through paths in the network at different probabilities (Qiao, Shan, & Zhou, 2017; Tutzauer, 2007).

In practice, researchers are encouraged to use proximity exposure to account for exposure to both direct friends and other peers who smoke. For example, interventionists may design network interventions to bring adolescents with high proximity exposure closer to currently distant nonsmokers, thereby increasing exposure to nonsmokers. Ultimately, this strategy may shift social norms and prevent tobacco use for these adolescents.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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References

Alexander C, Piazza M, Mekos D, & Valente TW (2001). Peers, schools, and adolescent cigarette smoking. Journal of Adolescent Health, 29, 22–30. 10.1016/S1054-139X(01)00210-5.

Bajaj S, & Nancy S (2019). Study of Gender Difference in Emotional Maturity among Adolescents. Journal of Exercise Science & Physiotherapy, 15(1). 10.18376/jesp/2019/v15/i1/111315.

Bandura A (1977). Social Learning Theory. Englewood Cliffs, NJ: Prentice-Hall.

Behler RL (2017). You can't always get what you want: network determinants of relationship inactualization in adolescence. Social Science Research, 61, 181–194. 10.1016/j.ssresearch.2016.06.012. [PubMed: 27886727]

Bountress K, Chassin L, Presson CC, & Jackson C (2016). The effects of peer influences and implicit and explicit attitudes on smoking initiation in adolescence. Merrill-Palmer Quarterly, 62(4), 335–358. 10.13110/merrpalmquar1982.62.4.0335.

Burk WJ, Steglich CE, & Snijders TA (2007). Beyond dyadic interdependence: Actor-oriented models for co-evolving social networks and individual behaviors. International Journal of Behavioral Development, 31(4), 397–404. 10.1177/0165025407077762.

Burt R (2010). The shadow of other people: Socialization and social comparison in marketing. In Wuyts SHK, Dekimpe MG, Gijsbrechts E, & Pieters FGM (Eds.), The connected customer: The changing nature of consumer and business markets (pp. 217–256). New York: Routledge.

Coban FR, Kunst AE, Van Stralen MM, Richter M, Rathmann K, Perelman J, Alves J, Federico B, Rimpelä A, Lorant V, Kuipers MA (2019). Nicotine dependence among adolescents in the European Union: How many and who are affected? Journal of Public Health, 41(3), 447–55. 10.1136/tobaccocontrol-2018-054244. [PubMed: 30192963]

Cressey DR (1978). Criminological theory, social science, and the repression of crime. Criminology, 16(2), 171–191. 10.1111/j.1745-9125.1978.tb00086.x.

Dijkstra JK, Cillessen AH, & Borch C (2013). Popularity and adolescent friendship networks: Selection and influence dynamics. Developmental Psychology, 49(7), 1242. 10.1037/a0030098. [PubMed: 22985296]

Ennett ST, Faris R, Hipp J, Foshee VA, Bauman KE, Hussong A, & Cai L (2008). Peer smoking, other peer attributes, and adolescent cigarette smoking: A social network analysis. Prevention Science, 9(2), 88–98. 10.1007/s11121-008-0087-8. [PubMed: 18404380]

Fujimoto K, & Valente TW (2012). Social network influences on adolescent substance use: disentangling structural equivalence from cohesion. Social Science & Medicine, 74(12), 1952–1960. 10.1016/j.socscimed.2012.02.009. [PubMed: 22475405]

Fujimoto K, Wang P, & Valente TW (2013). The decomposed affiliation exposure model: A network approach to segregating peer influences from crowds and organized sports. Network Science, 1(2), 154–169. 10.1017/nws.2013.7.

Furnham A, & Milner R (2017). Parent's beliefs and behaviours about the economic socialisation, through allowances/pocket money, of their children. Psychology, 8(08), 1216. 10.4236/psych.2017.88078.

Gentzke AS, Creamer M, Cullen KA, Ambrose BK, Willis G, Jamal A, & King BA (2019). Vital signs: tobacco product use among middle and high school students—United States, 2011–2018. Morbidity and Mortality Weekly Report, 68(6), 157. 10.15585/mmwr.mm6806e1. [PubMed: 30763302]

Gold DR, Wang X, Wypij D, Speizer FE, Ware JH, & Dockery DW (1996). Effects of cigarette smoking on lung function in adolescent boys and girls. New England Journal of Medicine, 335(13), 931–937. 10.1056/NEJM199609263351304.

Hoffman BR, Monge PR, Chou C-P, & Valente TW (2007). Perceived peer influence and peer selection on adolescent smoking. Addictive behaviors, 32(8), 1546–1554. 10.1016/j.addbeh.2006.11.016. [PubMed: 17188818]

Hooper D, Coughlan J, & Mullen MR (2008). Structural equation modelling: guidelines for determining model fit. Electronic Journal of Business Research Methods, 6(1), 53–60.

Hsieh CS, Van Kippersluis H. (2018). Smoking initiation: Peers and personality. Quantitative Economics, 9(2), 825–63.

Koutra D, & Faloutsos C (2017). Individual and collective graph mining: principles, algorithms, and applications. Synthesis Lectures on Data Mining and Knowledge Discovery, 9(2), 1–206. 10.2200/S00796ED1V01Y201708DMK014.

Kwok O-M, Cheung MW, Jak S, Ryu E, & Wu J-Y (2018). Recent advancements in structural equation modeling (sem): From both methodological and application perspectives. Frontiers in psychology, 9, 1936. 10.3389/fpsyg.2018.01936. [PubMed: 30356842]

Lejuez CW, Aklin WM, Bornovalova MA, Moolchan ET (2005). Differences in risk-taking propensity across inner-city adolescent ever-and never-smokers. Nicotine & Tobacco Research, 7(1), 71–9. 10.1080/14622200412331328484 [PubMed: 15804679]

Mayeux L, Sandstrom MJ, & Cillessen AH (2008). Is being popular a risky proposition? Journal of Research on Adolescence, 18(1), 49–74. 10.1111/j.1532-7795.2008.00550.x.

Mercken L, Steglich C, Sinclair P, Holliday J, & Moore L (2012). A longitudinal social network analysis of peer influence, peer selection, and smoking behavior among adolescents in British schools. Health Psychology, 31(4), 450. 10.1037/a0026876. [PubMed: 22251218]

Michell L (1997). Loud, sad or bad: young people's perceptions of peer groups and smoking. Health education research, 12(1), 1–14. 10.1093/her/12.1.1-a. [PubMed: 10166897]

Montgomery SC, Donnelly M, Bhatnagar P, Carlin A, Kee F, & Hunter RF (2020). Peer social network processes and adolescent health behaviors: a systematic review. Preventive Medicine, 130, 105900. 10.1016/j.ypmed.2019.105900. [PubMed: 31733224]

Munshi T, Heckman CJ, & Darlow S (2015). Association between tobacco waterpipe smoking and head and neck conditions: a systematic review. The Journal of the American Dental Association, 146(10), 760–766. 10.1016/j.adaj.2015.04.014. [PubMed: 26409986]

Newsom JT (2015). Longitudinal structural equation modeling: A comprehensive introduction. New York: Routledge.

Payne DC, & Cornwell B (2007). Reconsidering peer influences on delinquency: Do less proximate contacts matter? Journal of Quantitative Criminology, 23(2), 127–149. 10.1007/s10940-006-9022-y.

Pearson M, & West P (2003). Drifting smoke rings: Social network analysis and markov processes in a longitudinal study of friendship groups and risk-taking. Connections, 25(2), 59–76.

Perrine CG, Pickens CM, Boehmer TK, King BA, Jones CM, DeSisto CL, … Shamout M (2019). Characteristics of a multistate outbreak of lung injury associated with e-cigarette use, or vaping—United States, 2019. Morbidity and Mortality Weekly Report, 68(39), 860. 10.15585/mmwr.mm6839e1. [PubMed: 31581168]

Popa M (2012). The effects of tobacco smoking on the health of adolescents and young adults. Journal of Hygiene and Public Health, 62, 42–51.

Qiao T, Shan W, & Zhou C (2017). How to identify the most powerful node in complex networks? A novel entropy centrality approach. Entropy, 19(11), 614. 10.3390/e19110614.

Selfhout M, Burk W, Branje S, Denissen J, Van Aken M, & Meeus W (2010). Emerging late adolescent friendship networks and Big Five personality traits: A social network approach. Journal of personality, 78(2), 509–538. 10.1111/j.1467-6494.2010.00625.x. [PubMed: 20433629]

Simons-Morton BG, Farhat T. (2010). Recent findings on peer group influences on adolescent smoking. The journal of primary prevention. 31(4), 191–208. [PubMed: 20614184]

Tutzauer F (2007). Entropy as a measure of centrality in networks characterized by path-transfer flow. Social networks, 29(2), 249–265. 10.1016/j.socnet.2006.10.001.

Valente TW (2005). Network models and methods for studying the diffusion of innovations. In Carrington PJ, Scott J, & Wasserman S (Eds). Models and methods in social network analysis, 28, 98. (pp. 98–115). New York: Cambridge University Press.

Valente TW, & Foreman RK (1998). Integration and radiality: Measuring the extent of an individual's connectedness and reachability in a network. Social networks, 20(1), 89–105. 10.1016/S0378-8733(97)00007-5.

Valente TW, Gallaher P, & Mouttapa M (2004). Using social networks to understand and prevent substance use: A transdisciplinary perspective. Substance use & misuse, 39(10–12), 1685–1712. 10.1081/JA-200033210. [PubMed: 15587948]

Wang C, Hipp JR, Butts CT, & Lakon CM (2018). The interdependence of cigarette, alcohol, and marijuana use in the context of school-based social networks. PloS one, 13(7). 10.1371/journal.pone.0200904.

World Health Organization. Child & Adolescent Health Research Unit. Tobacco use in adolescence. (2016). Retrieved from http://www.euro.who.int/__data/assets/pdf_file/0016/303532/HBSC-No.7_factsheet_Tobacco.pdf?ua=1 Accessed 5 May 2020.

Highlights

- Proximity exposure: exposure to certain people in social networks based on distance
- Exposure to smokers by proximity (proximity exposure) predicts adolescent smoking
- This prediction persists, even in the absence of friends who smoke
- Peer influence by proximity is a more powerful process than peer selection
- Early proximity exposure predicts later cohesion exposure (befriending smokers)

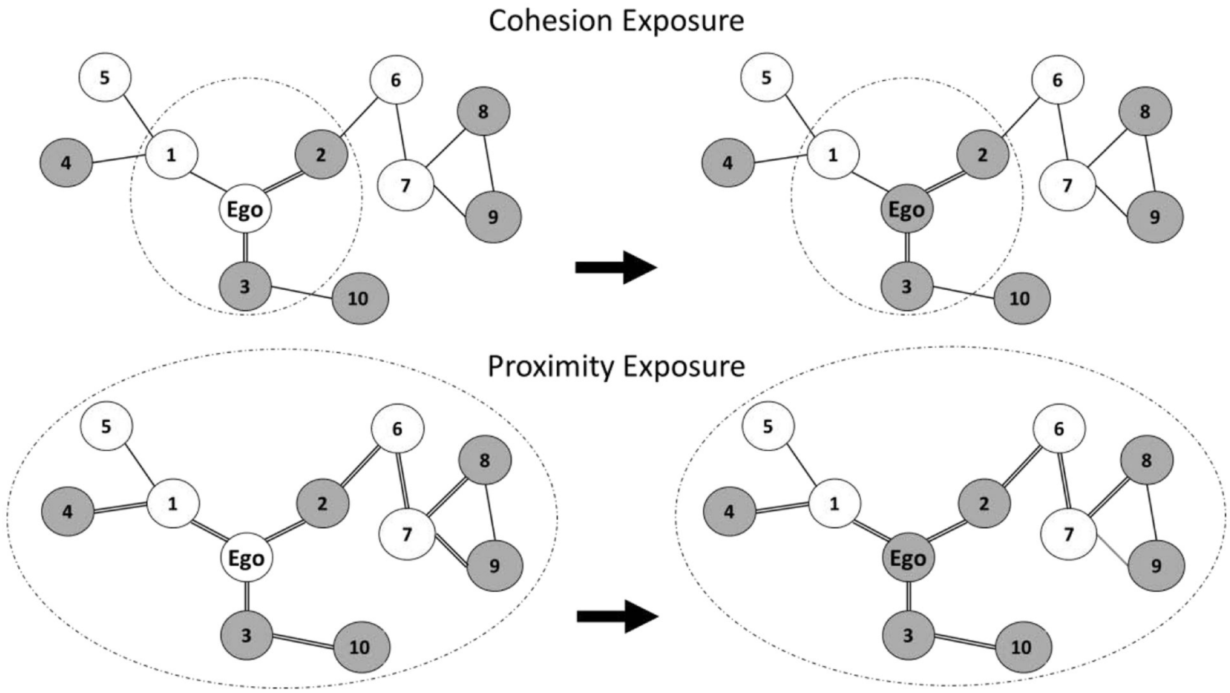

Figure 1. Presentation of cohesion exposure and proximity exposure as mechanisms of contagion.
Grey nodes indicate smokers, while white nodes indicate nonsmokers. Double-lines indicate connections being considered when measuring cohesion and proximity exposures. Dashed boundary indicates boundary of the network being considered when measuring cohesion and proximity exposures.

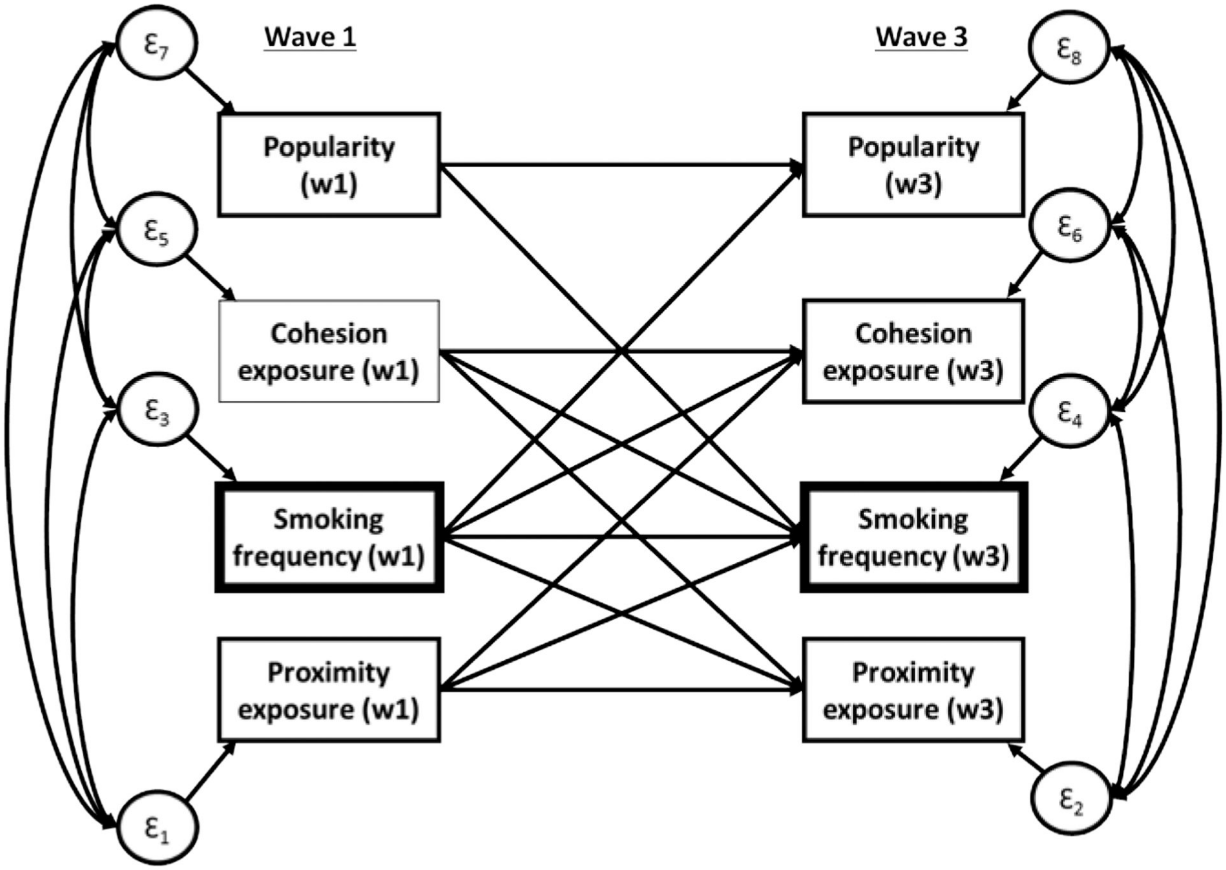

Figure 2. Hypothesized model of peer influence.

Epsilon indicates error terms. The exogenous variables (i.e., age, gender, smoking at home, and socio-economic status) will also be included.

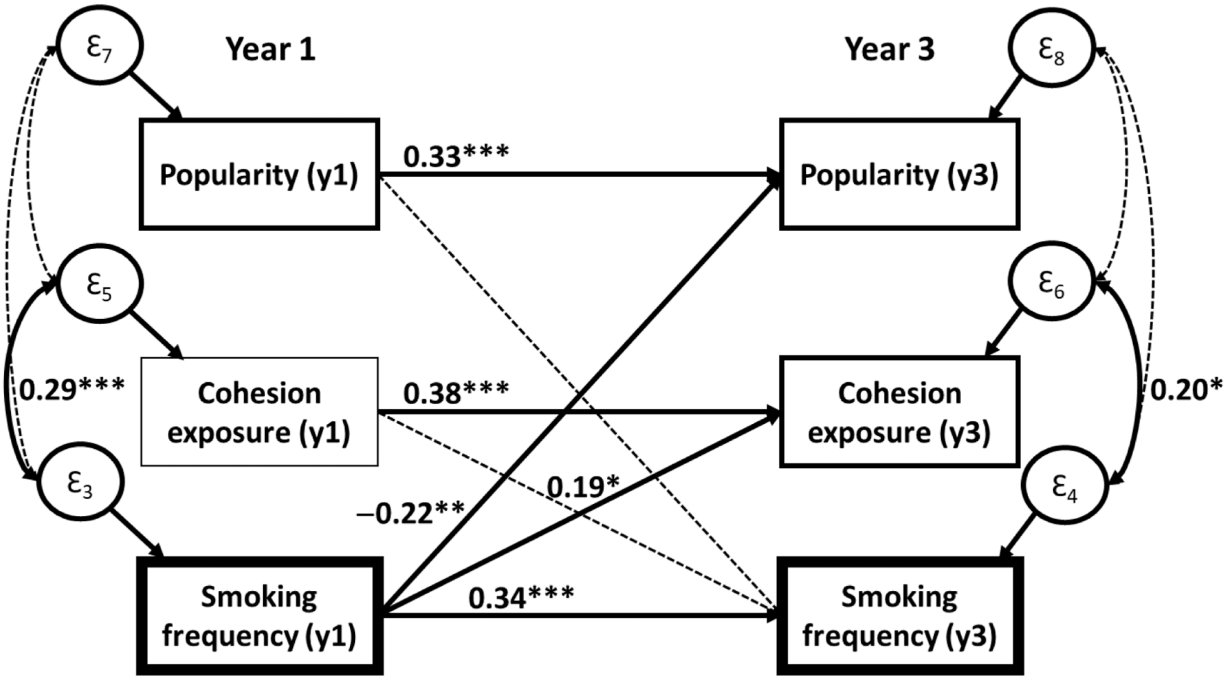

Figure 3. A Two-Year Panel Cross-lagged Path Model without Proximity Exposure Predicting Smoking Behavior.

Coefficients indicate standardized beta coefficients. Thin dashed arrows represent nonsignificant relationships. Only coefficients for significant relationships are presented. Epsilon indicates error terms. Appendix D presents the full model with its exogenous variables (i.e., age, gender, smoking at home, and socio-economic status). "y1" and "y3" indicate "Year 1" and "Year 3", respectively. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

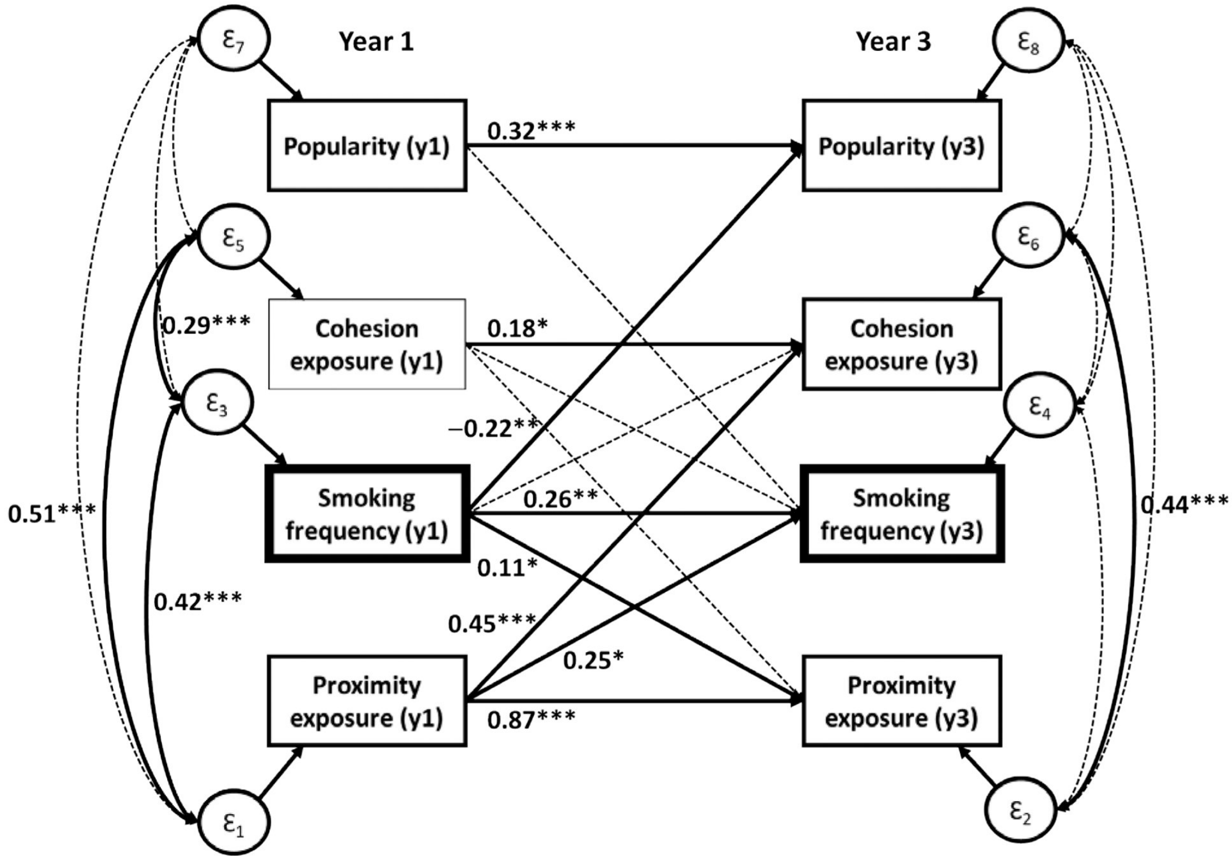

Figure 4. A Two-Year Panel Cross-lagged Path Model with Proximity Exposure Predicting Smoking Behavior.

Coefficients indicate standardized beta coefficients. Thin dashed arrows represent nonsignificant relationships. Only coefficients for significant relationships are presented. Epsilon indicates error terms. “y1” and “y3” indicate “Year 1” and “Year 3”, respectively. Appendix D presents the full model with its exogenous variables (i.e., age, gender, smoking at home, and socio-economic status). *p < 0.05, **p < 0.01, ***p < 0.001.

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Table 1:

Associations to be tested in the current study

Network positions predicting smoking behavior	Smoking behavior predicting network positions
Peer influence by popularity: Prior popularity will predict subsequent smoking behavior.	Perceived norms: Prior smoking behavior will predict stronger or weaker subsequent popularity.
Peer influence by cohesion exposure: Prior cohesion exposure will predict subsequent smoking behavior.	Friendship selection based on similar behavior (i.e., smoking): Prior smoking behavior will predict subsequent cohesion exposure
Peer influence by proximity exposure: Prior proximity exposure will predict subsequent smoking behavior.	Friendship selection based on proximity to individuals with similar behavior (i.e., smoking): Prior smoking behavior will predict subsequent proximity exposure
Convergence: Prior proximity exposure will predict subsequent cohesion exposure	

Note. Popularity is the number of friendship nominations received; cohesion exposure is the proportion of friends who smoke; proximity exposure is the proportion and proximity level of all smokers in the network.

Table 2:

Characteristics of Participants at Year 1 and Year 3 (N = 160)

	Year 1	Year 3	p-value
Age; in years, Mean (SD)	13.35 (0.33)	-	-
Gender, being female; n (%)	76 (47.50)		
Pocket money in British pounds; Mean (SD)	8.04 (6.89)	-	-
Having anyone else smoking at home; n (%)	65 (40.63)	-	-
Smoking behavior, being a smoker; n (%)[a]	20 (15.27)	37 (28.24)	< 0.001
Popularity[b]; Mean (SD)	0.04 (0.002)	0.03 (0.002)	0.001
Cohesion exposure[c]; Mean (SD)	13.88 (1.99)	26.36 (2.92)	< 0.001
Proximity exposure[c]; Mean (SD)	11.04 (0.30)	24.75 (0.38)	< 0.001

Note. Years 1 and 3 were compared using t-test statistics for continuous variables and Chi square tests for categorical variables.

[a]Both occasional and regular smokers are considered smokers.

[b]Popularity is measured with in-degree centrality.

[c]Cohesion exposure and proximity exposure can range from 0 to 100.