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High and Low Neurobehavior Disinhibition Clusters within Locales: Implications for Community Efforts to Prevent Substance Use Disorder

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Abstract

Background—Knowledge of where substance use and other such behavioral problems frequently occur has aided policing, public health, and urban planning strategies to reduce such behaviors. Identifying locales characterized by high childhood neurobehavioral disinhibition (ND), a strong predictor of substance use and consequent disorder (SUD), may likewise improve prevention efforts.

Objectives—The distribution of ND in 10–12-year olds was mapped to metropolitan Pittsburgh, PA, and tested for clustering within locales.

Methods—The 738 participating families represented the population in terms of economic status, race, and population distribution. ND was measured using indicators of executive cognitive function, emotion regulation, and behavior control. Innovative geospatial analyzes statistically tested clustering of ND within locales while accounting for geographic barriers (large rivers, major highways), parental SUD severity, and neighborhood quality.

Results—Clustering of youth with high and low ND occurred in specific locales. Accounting for geographic barriers better delineated where high ND is concentrated, areas which also tended to be characterized by greater parental SUD severity and poorer neighborhood quality.

Conclusions and Significance—Offering programs that have been demonstrated to improve inhibitory control in locales where youth have high ND on average may reduce youth risk for SUD and other problem behaviors. As demonstrated by the present results, geospatial analysis of youth risk factors, frequently used in community coalition strategies, may be improved with greater statistical and measurement rigor.

Keywords

disinhibition; children; geospatial analysis; substance use

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Declaration of Interest

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of this paper.

INTRODUCTION

Neurobehavioral disinhibition (ND) (a deficit in self-control of impulses) presages substance use and substance use disorder (SUD), their correlated behavior problems (e.g., antisocial behavior, gambling, risky sex) (1,2), and other SUD risk factors (3,4). Compared with same-aged peers, youths with ND are five times as likely to receive drug offers (5), less likely to consider the possible negative outcomes of substance use (6,7), and more likely to be placed in settings where deviancy reinforcement likely occurs (e.g., school detention, summer school) (8,9).

Prevalence of substance use, SUD, and other problem behaviors varies by geographic region (10,11). Locating areas where problem behaviors cluster informs policing, public health, and urban planning strategies to ameliorate such behaviors (11,12). Likewise, although geospatial research on ND is lacking, locating areas that are characterized by youth with ND could potentially inform where prevention programs are (not) needed to ameliorate SUD risk that arises from ND.

One approach to prevention relies on community leaders to determine which risk factors to target in community intervention (13). Statistical testing of clustering of risk factors within locales is rarely, if ever, conducted by community leaders or their expert prevention consultants (14). In lieu of the statistical testing, community leaders cannot test whether an observed average level of a risk factor for an area could be due to chance (and thus if their intervention strategy may be misguided).

The present study tested whether high ND clusters into geographic locals. Supporting this hypothesis, Ridenour et al. (15) reported that neighborhood quality (level of fiscal and social resources located there) directly predicted ND while controlling for parental SUD severity. The association between poor neighborhood quality and later SUD is mediated by biophysiological characteristics including testosterone level, cortisol stability level, and genetic and other heritable factors that correlate with ND (16,17). Specifically in longitudinal analyzes of the present sample, risk for SUD at age 22 that is attributable to quality of neighborhood of a boy's residence up to age 10–12 was mediated by the boy's testosterone at ages 10–12 and 16 and transmissible liability at ages 10–12 and 16 (using Sobel's test) (16). A second hypothesis was that variance in ND scores would cluster geospatially after controlling for parental SUD severity and neighborhood quality (i.e., using multiple regression). This result would suggest that other characteristics which cluster geographically that were not measured herein (e.g., local quality of education, acceptance of ND, or availability of interventions for attention deficit-hyperactivity disorder) further contribute to ND etiology.

The third hypothesis was that accounting for geographic barriers (e.g., large rivers, highways) results in greater specification of which areas are deemed to be characterized by high or low ND. The sample was from a region where many geographic features partition residential areas. However, to date geospatial analysis of substance use has lacked methods to statistically examine how geographic barriers may affect geospatial estimates of the clustering of substance use or its risk factors. Because such barriers impede social interaction, they may mitigate social contagion such as peer introduction of substance use or other deviancy reinforcement among youth residing on either side of a barrier (9). Geographic barriers also frequently demarcate social barriers such as ethnic or cultural neighborhoods, economic strata, and local governing bodies (e.g., school boards). Accordingly, accounting for such barriers in geospatial analysis should better delineate locales characterized by homogeneous residents.

METHODS

Participants

The 738 youths recruited from the greater Pittsburgh, PA, area were 10–12-year-old biological offspring of men with either lifetime SUD consequent to using illegal drugs ($n = 321$), lifetime psychiatric diagnosis other than SUD ($n = 78$), or no adult onset axis I or axis II psychiatric disorder ($n = 339$). The study design and sampling methods of the original study are detailed elsewhere (1,18,19).

Because the population-level occurrence of SUD consequent to using an illegal drug may be as low as 10% (20), it is difficult to locate fathers with this diagnosis who have a current or past spouse and also have a healthy biological child between 10–12 years of age, all of whom are also willing to participate in longitudinal research. Several recruitment strategies were employed, including random digit dialing conducted by a market research firm, advertising in print media, and public service announcements in electronic media. Approximately 20% of the fathers with SUD were recruited after discharge from treatment. The same procedures were used to recruit men without SUD except recruiting from addiction-treatment facilities. Previous analyzes have revealed that the fathers with and without SUD closely resemble their respective populations (21).

In accord with the protocol approved by the institutional review board, study goals were described to each family member prior to the test session. Next, the father, mother, and offspring were escorted to private rooms where written informed consent was obtained from the parents and written assent from the child. They were all informed that their privacy was protected by a Certificate of Confidentiality issued by the National Institute on Drug Abuse. Special effort was made to ensure that the boys were not coerced to participate. Urine and breath samples were collected and analyzed before commencing the research protocol to ensure that data were not influenced by the acute effects of drugs or alcohol (including cannabis). At the age 10–12 wave, no participant was found to be under the influence during, or have consumed drugs or alcohol recently prior to, the interview. The protocol was administered in fixed order. Following completion of the evaluation, each family member was debriefed and paid for their time and travel expenses. Offsprings were re-evaluated at ages 12–14, 16, 19, and 22; however, only data from ages 10–12 were analyzed herein.

Exclusion criteria for sons and fathers were a history of neurological disease or injury; chronic, disabling, or life-threatening illness; uncorrectable sensory impairment; or history of psychosis. Physical anomalies indicative of fetal alcohol effects, documented by examination conducted by a trained nurse, or full-scale Wechsler intelligence quotient (IQ) less than 80 also excluded children from participating.

Because of the stringent criteria on who could participate, an extended recruitment period was needed, spanning 1989–2000. The sample was nevertheless apropos for geospatial analysis because the Pittsburgh area population was highly stable over this period. Indeed, median salaries of the 1990 and 2000 census tracts correlated by .94 ($p < .01$), and the proportion of tract residents that were Caucasian correlated by .96 ($p < .01$) between 1990 and 2000 (nearly all of the Pittsburgh population was either European-American or African-American in both censuses).

An important aspect of the sample for geospatial analysis is that it is representative of its population. Study participants represented well their respective census tracts. Participant race (0 = Caucasian; 1 = African-American) correlated by .73 ($p < .01$) with the proportion of race of their respective census tract. The socioeconomic status (SES) of the study participant's family (head of household income) correlated by .44 with their median census

tract SES (aggregate of census individuals' incomes) in spite of the different measures of SES and different age ranges (24–74 vs. older than 16 years, respectively). The ratio of study participants to total residents per tract (22) indicated that the sample was spatially uniform across the area with respect to the population.

The sample was largely male, Caucasian, of average intelligence (with a normal distribution), and had average disinhibition (also normally distributed) (Table 1). The SES of most families was in the middle class.

Instrumentation

Neurobehavioral Disinhibition—ND scores encompassed indicators of affect regulation, behavior control, and executive cognitive capacity that have been described elsewhere (1,23,24). Affect regulation was measured in terms of temperament using the Revised Dimensions of Temperament Survey (25). Behavior control consisted of maternal and teacher ratings of externalizing symptoms, respectively, using the Kiddie-SADS-E (26) and Disruptive Behavior Disorders Rating Scale (27). Cognitive disinhibition was measured using tasks that gauge executive cognitive function (Stroop, Porteus Mazes, vigilance, motor restraint, forbidden toys, and the Block Design subscale of the WISC-III-R) and was found previously to comprise a single factor (28). Item response theory and factor analysis methods were used to aggregate raw scores into single dimensions (both in terms of the four indicators and ND) with raw scores being standardized (onto a t-score scale) and equally weighted (1). An array of psychometric properties of the ND construct have been reported previously (1,15,24,28). The indicators of ND described previously loaded onto one factor (ND score), ND scores at age 10–12 discriminate between having and not having a father with an SUD that results from using an illegal drug, and ND scores predict receipt of psychiatric treatment by age 16 (1). An intraclass correlation of .45 between ND scores at ages 10–12 and age 16 demonstrated moderate long-term stability in ND (1). ND scores at ages 10–12 predict SUD by age 22 as well as psychosocial characteristics during adolescence that in turn predict SUD (15,24).

Parent SUD Severity—An expanded version of the Structured Clinical Interview for DSM-III-R (29) was administered to each parent. SUD diagnoses were consensually formulated in a clinical conference of a psychiatrist certified in addictions psychiatry (chair), another psychiatrist or psychologist, and the trained clinical interviewers. The variable analyzed herein was a continuous measure of SUD severity, taking into account all SUD diagnoses and derived using item response theory methods (30,31).

Neighborhood Quality—Previous measures of neighborhood frequently focus on either economic or social resources (32,33). Herein, both features of neighborhoods were measured and aggregated to statistically investigate the association between neighborhood and ND. Census data were used to measure neighborhoods, which are readily available to community leaders and other researchers. *Concentrated disadvantage* was the mean of the proportion of households in a neighborhood having the following: 1) total income below poverty; 2) a female as head of the household; 3) receiving public assistance; 4) having an unemployed parent; and 5) residents under 18 years of age (15). Standardized α was .95. *Residential instability* was the mean of two correlated variables ($r = .28, p < .001$): proportion of households with residents who moved since the preceding census and proportion of vacant houses (15). Consistent with the threshold used in factor analysis to determine whether factor loadings reflects a single latent construct (.3 or the more conservative .4), the correlation between concentrated disadvantage and residential instability of .52 ($p < .001$) indicated that a single latent factor contributed to them.

Accordingly, their mean score was used to index neighborhood quality (standardized $\alpha = .87$).

Geocoding

Geocoding links an individual participant's data to a corresponding location on a map (typically his/her residence). In effect, results of traditional analysis (e.g., prevalence rates, means) can be plotted on a map to understand trends related to geography, such as "red" versus "blue" states during the US election season. Traditional geospatial analyzes of substance use aggregates person-level data into area units (e.g., states, neighborhood-level averages, or census tracts).

However, aggregating data within areas assumes that people and spatial characteristics are homogenous within each unit and that they categorically differ from adjacent units (termed the Modifiable Areal Unit Problem). This assumption is appropriate for policy or voting (which are implemented according to area units) but is not valid for psychiatric or behavioral analysis. To illustrate this caveat with respect to social contagion, persons who reside on either side of a state line (e.g., residents of New York City, NY, and Newark, NJ) are presumed to be unlikely or less likely to interact compared with persons residing on opposite sides of the state (e.g., residents of New York City and Niagara Falls). This approach moreover reduces the analytic sample size of independent observations. Perhaps the most problematic upshot of this approach is that different clustering results can occur simply by relocating the boundaries of area units (e.g., as US politicians do to improve their chances of re-election) (34). Therefore, to avoid these caveats, data were geocoded according to residential address and analyzed as individual cases (i.e., pinpointed on a map) rather than as aggregated subsamples.

Analyzes

Analyzes were conducted following the steps of multiple regression. The goal of analyzes was to account for variability in ND using parental SUD and neighborhood quality as predictors. At each step in the regression analysis, the level of ND was plotted on a map of the greater Pittsburgh region (geocoded). By mapping the results, it is possible to learn where clusters of high (and low) ND occur as well as which of the predictors co-cluster in these locales. Statistical analyzes were conducted using SAS 9.3 (SAS Institute, Cary, NC); geospatial analyzes were conducted using ArcGIS 9.2 (35).

Geospatial Cluster Analysis—As with traditional analyzes (e.g., mean differences), simple inspection of geocoded results can be misleading; accompanying statistical tests provide greater rigor for determining the degree to which an effect might be due to chance. Three geospatial tests of whether ND levels cluster into locales were conducted: Local Moran's I, Getis-Ord Gi, and Spatial Scan (36–38). Because results were consistent among techniques, and Local Moran's I results are easily presented as localized z-scores, only Local Moran's I was presented. This method maps the degree to which nearby observations are more similar than distant ones (i.e., local autocorrelation) using z-scores such that large Moran's I scores correspond to high clustering.

Geographic Barriers—Traditional geospatial analyzes measure distance between participants linearly, "as the crow flies." This approach may overestimate clustering by failing to account for physical barriers between residential areas (e.g., a large river) which in effect separate people. Physical barriers were important to take into account because Pittsburgh has numerous large geographic partitions between residential areas, including 3 large rivers and 12 major highways.

To account for the effect of barriers when testing ND clustering, map pixels representing major barriers were superficially increased by 10-fold (39,40). Thus, the virtual “distance” between any two participants equaled the straight line between them with segments of the line over a major barrier weighted by 10.

Road and river data from the US National Atlas were downloaded from the US Geological Survey seamless data server (41). Map data for highways were obtained from the category “Limited Access Highways.” The newest of the highways was constructed prior to 1989. Map data for rivers were obtained from “Streams and Waterbodies of the United States.”

Map Output—Although analyzes utilized the residence as a participant’s map location, publishing such data could compromise participant confidentiality. Thus, results were presented using maps that were reformatted to also present geospatial trends more clearly (Figure 1). This reformatting used the Bailey-Gatrell (42) two-step process. First, individual participant’s ND scores (dots in Panel A) were first extrapolated in combination with nearby participants (using the ordinary Kriging method, 20 nearest neighboring points, and spatial resolution of 100 m). This process generates a map of color-coded results, similar to a topographical map, to represent the aggregate level of ND in an area (cf., the background of Panel B). Second, the edges of color coding were smoothed to eliminate spikes caused by outlier participants (cf., backgrounds of Panels B versus C). (Smoothing consisted of a moving window average filter with a 1 km circular diameter.)

RESULTS

ND Clustering

The geographic distribution of observed ND is presented in terms of ND scores (Figure 2). The statistical degree of clustering of ND is presented as a map of z-scores (Figure 3), which correspond to p values (cf., 1.96). Considering both maps simultaneously, statistical clustering of ND is greatest where the highest ND scores on average occur. A region due north of the City of Pittsburgh is characterized by lower-than-average ND.

Accounting for Geographic Barriers

Figure 4 presents statistical clustering results, accounting for physical barriers. Compared with Figure 3, ND clustering is more narrowly demarcated in certain locales (e.g., “A” and “B,” both characterized by high ND) and less so in others (e.g., “C,” characterized by low ND). Overall, accounting for geographic barriers reduced the areas that are deemed to be characterized by high ND.

Accounting for Parental SUD, Neighborhood Quality

Statistical clustering of ND overlaps with parental SUD severity and neighborhood quality (Figure 5, panels A and B, respectively). Inspection of the two maps suggests that neighborhood quality overall accounts for greater variability in ND than parental SUD severity (e.g., shades of gray are darker overall for parental SUD). However, each predictor accounts for ND variance in different regions, suggesting unique contributions of each predictor. Neighborhood quality also accounts for more ND variance where high ND clusters occur (e.g., at locales “A” and “B”).

Figure 6 maps ND variation, accounting for both predictors. Whereas some ND clustering remains unaccounted for, much of the overlap between ND and its predictors is linked to specific locations. Perhaps the most important result is that, when considering Figures 2 and 6 simultaneously, little of the clustering of ND remains unaccounted for in the locales that are characterized by high ND (the darker locales in Figure 2).

DISCUSSION

This study elucidated geographic clustering of ND, a well-documented childhood risk for SUD and other pathological behaviors, for metropolitan Pittsburgh. High and low levels of ND cluster in certain locales. Taking into account geographic barriers (rivers, highways) yielded more conservative demarcations of high ND clusters. Neighborhood quality and parental SUD severity accounted for clustering of ND in different locales. Little ND variance remained after accounting for the two predictors; nevertheless, some geographical clustering of the remaining ND variance was observed. Thus, because participants resided in their neighborhoods prior to measuring ND and it was previously found that ND fully mediated the association between neighborhood quality and SUD (15), the present geospatial results further support the conclusion that risk for SUD that is attributable to childhood neighborhood quality is accounted for by ND.

As mentioned earlier, separate efficacy studies suggest that reducing ND in youth could decrease risk for behavior problems including SUD (43–46). Evidence herein supports providing such programs at locales characterized by clustering of high ND to reduce SUD liability there. Local governments could support businesses providing the aforementioned activities, help advertise them (and disseminate research supporting those activities), and offer vouchers for youths with ND to receive the activities (perhaps in collaboration with school psychologists or pediatricians).

A critical first step in community-level efforts to implement prevention programs targeting behavior problems is measurement of the risk factor(s) that might be addressed during intervention (13,14). Measuring ND (as operationalized herein) would require considerable time, effort, and expense to evaluate community levels. In contrast, locales characterized by parents with SUD or neighborhood quality can be more readily identified (e.g., using records from SUD treatment programs or census data, respectively). Results herein suggest that the latter two variables provide proxy indicators of where clusters of youth with high ND reside. After identifying a locale, additional screening, advertisement, or assessment might be used to admit youth into prevention programs to reduce ND.

Prior evidence demonstrates that community coalition strategies at least at times generate little to no efficacy and can lead to iatrogenic outcomes (14). The analytic and measurement rigor described herein may more accurately identify locales with youth at high risk for problem behaviors due to a particular risk factor. This approach also could improve the allocation of what little resources can be committed to prevention in those locales where the impact could be greatest. In the case of ND, local governmental support of privatized programs that improve cognitive self-control would cost less, more likely target youth with ND, and be tailorable compared with universal intervention approaches often employed by community coalitions (47).

Accounting for parental SUD reduces statistical clustering of ND, suggesting that where high ND occurs so does severe parental SUD. Accordingly, for prevention to effectively reduce SUD risk that arises from ND, it may also require parental SUD treatment and/or recovery maintenance programs to manage ongoing familial SUD risk. Moreover, the partial overlap of parental SUD and neighborhood quality in accounting for ND (Figure 5, panels A and B) is consistent with the notion that statistical control for parental SUD also accounts for the effect(s) of parent SUD on subsequent familial social stratification/selection and residence locale (48).

Three study limitations were noted. The original data collection was not designed specifically for geospatial research. It was nevertheless fortuitous that participant residences resembled the Pittsburgh area population in distribution and important demographics.

Gender and race differences were not studied due to (a) a specific focus on the variables of greatest interest, (b) sample size limitations, and (c) large overlap between race and neighborhood quality (consistent with past studies) (32,33). Gender and race have previously been found to co-vary with geographic distribution of behavior problems including SUD (49), and measurement inequality has been found to occur between races (50). This study was confined to one component of SUD vulnerability, ND; geospatial analysis of additional risk factors may improve the geographic characterization of youth SUD risk (51,52).

To summarize, geospatial clustering of ND in 10–12-year olds was delineated for the greater Pittsburgh area. Specific locales were identified that are characterized by youth with high ND (which presages substance use and behavior problems). More broadly, study results demonstrated the ability and need to characterize geospatial locations in terms of risk factors for understanding the etiology and prevention of SUD. This line of research offers high potential for locating target populations in need of, and allocating resources for, SUD risk monitoring and prevention.

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FIGURE 1.

Process of smoothing point coordinate data to preserve participant confidentiality.

Note: Point coordinate data (Panel A) superimposed onto each subsequent panel for comparison to the interpolated (Panel B) and smoothed (Panel C) output.

FIGURE 2.
Geospatial distribution of ND throughout the greater Pittsburgh area.
Note: Darker areas represent greater ND, based on standard scores.

FIGURE 4.

Degree of geospatial clustering of ND throughout the greater Pittsburgh area, accounting for major geographic barriers.

Note: Compared with Figure 4, regions “A” and “B” have notably less clustering of high ND; region “C” has notably greater clustering of low ND.

FIGURE 5. Degree of geospatial clustering of residual ND. Panel A: Residual ND variance after accounting for parental SUD. Panel B: Residual ND variance after accounting for neighborhood quality.

FIGURE 6.
Residual ND variance after accounting for parental SUD and neighborhood quality.

TABLE 1

Sample characteristics.

Gender (male)	71.3%
Family economic status	40.9 (13.31)
IQ	106.9 (16.06)
Size of sibship	3.0 (1.24)
Neighborhood quality index	.2 (.09)
Neurobehavioral disinhibition	50.1 (10.23)
Paternal SUD consequent to using illegal drugs	43.5%
Psychiatric diagnosis in fathers other than SUD	10.4%
Ethnicity:	
Caucasian	75.1%
African-American	22.1
Other/biracial	2.7

Note: $n = 738$. Family socioeconomic status was measured using the Hollingshead Index. IQ was measured using the Wechsler Intelligence Scale for Children-III, Full Scale score. SUD = substance use disorder.