Neighborhood Typologies Associated with Alcohol Use among Adults in Their 30s: a Finite Mixture Modeling Approach

Isaac C. Rhew · Rick Kosterman · Jungeun Olivia Lee

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Abstract There has been increasing interest in how neighborhood context may be associated with alcohol use. This study uses finite mixture modeling to empirically identify distinct neighborhood subtypes according to patterns of clustering of multiple neighborhood characteristics and examine whether these subtypes are associated with alcohol use. Neighborhoods were 303 census block groups in the greater Seattle, WA, area where 531 adults participating in an ongoing longitudinal study were residing in 2008. Neighborhood characteristics used to identify neighborhood subtypes included concentration of poverty, racial composition, neighborhood disorganization, and availability of on-premise alcohol outlets and off-premise hard liquor stores. Finite mixture models were used to identify latent neighborhood subtypes, and regression models with cluster

robust standard errors examined associations between neighborhood subtypes and individual-level typical weekly drinking and number of past-year binge drinking episodes. Five neighborhood subtypes were identified. These subtypes could be primarily characterized as (1) high socioeconomic disadvantage, (2) moderate disadvantage, (3) low disadvantage, (4) low poverty and high disorganization, and (5) high alcohol availability. Adjusted for covariates, adults living in neighborhoods characterized by high disadvantage reported the highest levels of typical drinking and binge drinking compared to those from other neighborhood subtypes. Neighborhood subtypes derived from finite mixture models may represent meaningful categories that can help identify residential areas at elevated risk for alcohol misuse.

Keywords Finite mixture model · Neighborhood context · Alcohol · Latent class analysis

I. C. Rhew (✉)
Department of Psychiatry and Behavioral Sciences, Center for the Study of Health and Risk Behaviors, University of Washington, Box 354944, Seattle, WA 98195, USA
e-mail: rhew@uw.edu

R. Kosterman
Social Development Research Group, University of Washington, 9725 3rd Ave NE, Suite 401, Seattle, WA 98115, USA
e-mail: rickk@uw.edu

J. O. Lee
School of Social Work, University of Southern California, 669 W 34th St, Montgomery Ross Fisher, #325, Los Angeles, CA 90089, USA
e-mail: lee363@usc.edu

Introduction

The role of urban neighborhood context in the development of various health problems, including alcohol misuse, has become of significant research interest over the past two decades [1–3]. In regard to alcohol misuse, studies have observed that social environmental characteristics such as neighborhood socioeconomic disadvantage [4, 5] and disorganization [6, 7] are associated with alcohol use and misuse. Further, aspects of the built environment, namely, availability of alcohol outlets [8–10], have also been linked to alcohol misuse. The

majority of studies examining neighborhood factors have examined a single neighborhood characteristic at a time, which may be in part due to challenges when examining joint contributions of multiple neighborhood factors such as “structural confounding,” where levels of covariates are not represented across all levels of the exposure likely due to social forces [11, 12]. However, a traditional risk factor framework that seeks to identify and isolate independent effects of variables may overlook the “causal architecture” of how multiple co-occurring factors may interact to contribute to common public health problems including alcohol misuse [13].

Alternative methods may be useful in this regard. Finite mixture models such as latent class analysis and latent profile analysis are now widely used in behavioral health research to empirically identify distinct underlying subpopulations of individuals with similar patterns according to multiple indicators [14]. Mixture models, often referred to as “person-centered” methods, assume that the joint distribution of the multiple indicators results from a mixture of two or more distinct homogeneous subpopulations. This approach is somewhat analogous to traditional factor analysis except that the factor in question is a categorical rather than continuous variable.

Researchers have begun to extend this mixture modeling approach to “neighborhood-centered” studies. For example, one study identified five distinct subgroups of neighborhoods that differed non-uniformly according to levels of residential density, availability of retail and transit, access to recreational facilities, pedestrian and bicycle infrastructure, and safety. This study found that those living in two neighborhood subtypes were distinguished as having high levels of all features and those characterized specifically by high density and high retail and transit availability engaged in more physical activity [15]. This method could be extended to identify subtypes related to alcohol misuse. Such an approach may clarify how multiple features cluster to yield underlying forms of residential environments that contribute to alcohol problems and thus help public health practitioners and urban planners identify areas of greatest need of intervention and consider appropriate area-level interventions.

This study uses finite mixture modeling as a method to identify neighborhood subtypes that may be related to alcohol use. Five neighborhood characteristics that have been theorized or observed to be associated with alcohol use were used as indicators to derive the latent

neighborhood classes: (1) percentage of residents living in poverty, (2) percentage of residents of White race, (3) perceived neighborhood disorganization, (4) availability of on-premise alcohol outlets (e.g., bars), and (5) availability of off-premise liquor outlets. Alcohol use outcomes were then compared among individuals living in these different latent classes of neighborhoods, adjusted for covariates.

Methods

Participants

Individual-level data were from the Seattle Social Development Project (SSDP), a longitudinal study examining the etiology of substance use problems and their associated behavior problems. This study has followed a cohort of 808 individuals recruited in the fifth grade in 1985 from public elementary schools that overrepresented high-crime areas in Seattle. For this study, we used cross-sectional data from 531 (65.7%) participants who were living in King County in WA, USA, at a study assessment conducted in 2008 when participants were approximately 33 years old. Neighborhoods were defined as the census block groups in which the participants resided at the time of this survey. Studies suggest that these represent meaningful geographic boundaries for identifying area-level differences for a variety of health indicators [16]. Residential addresses were geocoded, and the census block groups for those addresses were determined. Across the sample, 303 block groups were included with an average of 1.8 participants per block group (range 1 to 3). This study was approved by the University of Washington Institutional Review Board.

Neighborhood Measures

Census block group percentage of residents living in poverty and percentage of residents of White race were obtained from data from the American Community Survey (ACS) of the US Census. Although the ACS collects annual data on these characteristics, year-specific estimates are unstable due to small sample sizes, and thus, 5-year averages are recommended. Averages for 2007 to 2011 were used for this study.

Neighborhood disorganization was assessed using a self-reported measure from the individual participants.

The scale asks participants to rate eight different problems from 0 (not at all) to 3 (a lot) on how much they describe their neighborhoods (e.g., crime or drug selling, fights, shootings, graffiti). The item scores were summed to create a total disorganization score (Cronbach's $\alpha = .93$). For census block groups with more than one participant, the scale scores of the individuals within that block group were averaged.

Availability of alcohol outlets within the census block group was assessed using King County tax parcel data and business and telephone listings based on records from 2009. The count of on-premise outlets and hard liquor off-premise outlets located within block groups was calculated. On-premise outlets were defined as drinking establishments where alcohol could be consumed on site and a majority of the sales was due to alcohol (e.g., bars, pubs, taverns, sports bars). For this study, off-premise hard-liquor outlets were locations where hard liquor was sold but could not be consumed on site. We focused on hard liquor rather than any alcohol off-premise outlets because at the time of the survey, hard liquor was sold only in state-run stores in WA and because of research suggesting the potential impact of liquor stores on alcohol-related harms [17]. The vast majority of neighborhoods (>80%) in this study contained no on- or off-premise outlets. Thus, both on- and off-premise outlet availability variables were coded as dichotomous (0: no outlets; 1: one or more).

Individual Measures

For individual-level data, surveys were conducted either via an in-person interview, telephone interview by a trained interviewer, or online survey. The entire assessment was approximately 2 hours in length. Typical number of drinks consumed per week was ascertained based on the sum of the typical number of drinks consumed during weekdays (Monday through Thursday) and during weekends (Friday through Sunday). For number of binge drinking episodes, participants were asked to report the number of times they had five or more drinks in one sitting in the past year. Additional demographic characteristics were assessed, including gender, race/ethnicity, and annual household income.

Data Analyses

Finite mixture modeling (FMM) was used to identify the subtypes, or classes, of the 303 neighborhoods

according to the neighborhood indicators described above. The first step in the FMM was to determine the appropriate number of classes. Five separate models were performed specifying different numbers of latent classes to be extracted, from 2 to 6. Because no single test is sufficient, the fit of the models was compared using a variety of approaches including Akaike's Information Criteria (AIC), Bayesian Information Criteria (BIC), entropy (a measure ranging from 0 to 1 of how distinct the identified classes are from one another with values closer to 1 indicating greater distinction), and likelihood ratio tests [14]. Further, descriptive statistics for the classes were considered to assess whether classes yielded meaningful distinctions. The FMM models were performed in Mplus, version 7, using maximum likelihood with robust (MLR) standard error estimation.

After selecting the appropriate number of meaningful classes, analyses examined associations between the identified neighborhood classes and the alcohol outcomes among individuals. For each unit (here, neighborhood), FMM models yield posterior probabilities for membership in each of the classes. In order to account for these probabilities, a "pseudo draw" approach was used where the posterior probabilities were used to assign each neighborhood to a class 40 times [18]. For example, if a neighborhood's posterior probability for membership in a given class were .80, then this neighborhood would be assigned to this class approximately 32 of the 40 draws. The individual-level data of the 531 participants were then linked to the 40 draws for the class assignments for their neighborhoods.

Similar to analyses using multiply imputed data, regression models were performed for each of the 40 draws and results were then combined across the 40 draws using Rubin's rules in order to account for the uncertainty of class membership [19]. In regression models, the neighborhood latent class categorical variable was entered as dummy variables. Additional covariates included gender, race (White, African American, other), and annual household income. The alcohol outcomes, typical drinks per week, and number of binge drinking episodes were discrete non-negative integers that showed a positive skew. Thus, they were treated as count variables using over-dispersed Poisson models. In count regression models, coefficients are connected to the outcome via a log link and are often exponentiated to yield count ratios (CRs; also often referred to as rate ratios) that describe the proportional increase in the count associated with a one-unit increase in the

covariate [20]. To account for clustering of individuals within neighborhoods, cluster robust standard errors were estimated. Regression analyses were conducted in R statistical software [21] using the “multiwayvcov” package [22] to perform the cluster robust generalized linear models and the “mitools” package [23] to combine results over the 40 draws.

Results

Table 1 provides descriptive statistics for demographic characteristics and the outcome variables for the individuals in this sample. The mean number of typical drinks per week was 5.8 (SD = 8.2), and the mean number of days per year engaging in heavy episodic drinking was 7.7 (SD = 22.6). Descriptive information for characteristics of the 303 neighborhoods represented in this study is shown in Table 2.

Although fit statistics seemed to indicate better model fit for a six-class solution based on a lower AIC and BIC and higher entropy relative to other models as well as a statistically significant likelihood ratio test comparing the six-class to five-class solution ($p < .001$), the five-class solution was ultimately selected. One reason for this is that the sizes of certain classes in the six-class solution were small, and detecting differences in alcohol outcomes would be difficult. Further, comparison of distribution of the indicators across latent class suggested the additional class in the six- vs. five-class

Table 1 Demographic and alcohol-related characteristics for individual participants

Characteristic	<i>N</i> = 531 % or mean (SD)
Race	
White	41.1
Black	28.1
Other	30.9
Female sex	48.8
Annual household income	
<\$35,000	25.6
\$35,000–\$49,999	13.4
\$50,000–\$74,999	22.0
≥\$75,000	38.1
Typical drinks per week	5.8 (8.2)
Number of binge drinking days in past year	7.7 (22.6)

Table 2 Characteristics of study neighborhoods

Characteristic	<i>N</i> = 303 Mean (SD) or %
Percentage living in poverty	11.7 (11.2)
Percentage White race	64.5 (21.4)
Neighborhood disorganization	5.2 (5.0)
Any on-premise alcohol outlet, %	26.7
Any off-premise liquor outlet, %	17.5

model only varied along the continuum of the continuous social environmental neighborhood indicators that already defined three of the classes in the five-class solution (described below) and would not be particularly distinct or meaningful.

Table 3 displays the observed distribution of the neighborhood indicators across the five neighborhood latent classes assigned according to the highest posterior probability. Compared to the other classes, class 1 neighborhoods (4.0% of the neighborhoods) tended to have the highest levels of poverty and disorganization and had a lower composition of White residents. Class 2 neighborhoods (11.6%) had moderate levels of poverty and disorganization and had a low percentage of White residents. Class 3 neighborhoods (69.3%) were the most common and had low levels of poverty and disorganization and were predominantly White race. Class 4 neighborhoods (5.0%) tended to have low levels of poverty, but high levels of disorganization; these neighborhoods also had a moderate percentage of White residents. In regard to alcohol outlet availability, neighborhoods in classes 1 thru 4 had a lower likelihood of having an on- or off-premise alcohol outlet compared to class 5. Class 5 neighborhoods (10.2%) were very likely to have an on-premise and off-premise alcohol outlet and also relatively low levels of poverty, a high percentage of White residents, and low levels of disorganization. Based on the distributions of indicators, the classes were labeled as follows: class 1: high disadvantage (HiDis), class 2: moderate disadvantage (ModDis), class 3: low disadvantage (LoDis), class 4: low poverty and high disorganization (LoPov/HiDisorg), and class 5: high alcohol availability (HiAlc).

Alcohol outcomes were compared across residents of these latent neighborhood classes. Descriptive statistics showed that individuals from HiDis neighborhoods had notably higher levels of typical drinking and binge drinking compared to those from other neighborhood

Table 3 Distribution of neighborhood characteristics by latent classes

	1 HiDis	2 ModDis	3 LoDis	4 LoPov/HiDisorg	5 HiAlc
Mean % living in poverty	44.3	28.7	7.1	9.3	11.4
Mean % White	48.0	47.3	67.3	59.1	74.4
Mean neighborhood disorganization	15.9	6.8	3.4	15.5	6.3
Any on-premise outlet, %	33.3	34.3	16.2	0.0	100.0
Any off-premise outlet, %	33.3	17.1	3.8	40.0	93.5

Neighborhoods assigned according to the highest probability of class membership

HiDis high disadvantage, *ModDis* moderate disadvantage, *LoDis* low disadvantage, *LoPov/HiDisorg* low poverty and high disorganization, *HiAlc* high alcohol availability

subtypes. Thus, the HiDis class was selected as the referent group in the regression models. Consistent with the descriptive findings, results from adjusted regression models showed that compared to those residing in HiDis, individuals from other neighborhood classes (2 thru 5) reported fewer typical number of drinks per week (Table 4). These differences compared to the HiDis neighborhoods were all statistically significant except for the LoPov/HiDisorg neighborhood. A similar pattern was observed when examining binge drinking as the outcome. Compared to individuals from HiDis neighborhoods, those living in other classes of neighborhoods reported less binge drinking. Although CRs were low for each of the classes, statistically significant

differences compared to HiDis neighborhoods were observed only for ModDis (CR = .21; 95% CI .05, .84) and LoDis (CR = .29; 95% CI .11, .79) neighborhoods.

Discussion

Using a finite mixture modeling approach, we empirically identified five distinct subtypes of neighborhoods according to multiple neighborhood characteristics that have been observed in prior research to be related to alcohol misuse. Three of these classes appeared to vary along the continuum of social environmental indicators but were similar in regard to having relatively low

Table 4 Count ratios and 95% confidence intervals for typical drinks per week and number of binge drinking episodes in the past year according to neighborhood class and other covariates

	Typical drinks per week		Binge drinking episodes in past year	
	CR	95% CI	CR	95% CI
Neighborhood class				
1: HiDis (ref)	—	—	—	—
2: ModDis	.43	.23, .80	.21	.05, .84
3: LoDis	.48	.30, .79	.29	.11, .79
4: LoPov/HiDisorg	.53	.26, 1.08	.32	.09, 1.16
5: HiAlc	.52	.28, .96	.32	.09, 1.13
Female sex	.40	.31, .51	.22	.10, .48
Income	.99	.96, 1.01	.99	.94, 1.05
Race				
White (ref)	—	—	—	—
Black	.86	.64, 1.18	.88	.41, 1.89
Other	.80	.60, 1.07	1.25	.70, 2.24

HiDis high disadvantage, *ModDis* moderate disadvantage, *LoDis* low disadvantage, *LoPov/HiDisorg* low poverty and high disorganization, *HiAlc* high alcohol availability

alcohol outlet availability compared to the HiAlc class. One class, LoPov/HiDisorg, was distinct in that it had relatively low levels of poverty but high levels of perceived disorganization. The final class, HiAlc, was distinct in that it had a very high probability of having an on-premise outlet and hard-liquor outlet.

Weekly and binge drinking results from this study suggest that these empirically identified groups may be meaningful with respect to alcohol behaviors. When comparing alcohol outcomes across individuals from these different neighborhood subtypes, results suggested that elevated alcohol use was the most concentrated among those from the neighborhood class primarily characterized by high levels of poverty and disorganization and low percentage of White race (HiDis). Interestingly, those living in neighborhoods primarily characterized by the presence of on-premise outlets and hard liquor retail outlets did not show elevated alcohol use.

In reviewing the characteristics of the neighborhood classes identified, it is notable how neighborhood-level poverty, racial composition, and disorganization clustered together, particularly for classes 1 thru 3. These classes were similar in having notably lower probabilities of availability of alcohol outlets compared to the HiAlc class (1), but differed in the relative levels of social environmental indicators from class 1 to class 3, in order, such that there was decreasing levels of poverty, increasing levels of percent White race, and decreasing levels of disorganization from class 1 to class 3.

The finding that residents of neighborhood classes characterized by socioeconomic disadvantage and disorganization had the highest level of typical and high-risk alcohol use is consistent with other research literature. A number of studies have observed associations between neighborhood socioeconomic disadvantage and problem alcohol use [4]. Disadvantaged and disorganized neighborhood environments may influence individual-level alcohol use through various mechanisms, including the presence of psychosocial stressors within the environment that may cause individuals to drink alcohol in order to cope, as well as a lack of material and social resources to buffer against various individual daily hassles as well as environmental stressors.

It is noteworthy that the other classes showed similar differences in alcohol outcomes compared to the HiDis class. Although the LoPov/HiDisorg class was relatively high in neighborhood disorganization, residents of this

neighborhood subtype appeared to engage in lower levels of typical and binge drinking, which may suggest that it is the joint combination of both socioeconomic disadvantage and disorganization rather than perceived disorganization on its own that contributes to alcohol use.

The finding that residents of HiAlc neighborhoods more characterized by the likely presence of alcohol outlets were not elevated in typical or binge drinking may on its surface be surprising given the literature suggesting the role of alcohol outlet availability on alcohol use [24, 25]. However, it is important to note that, at the time of this study, WA, where the study neighborhoods were located, regulated the sales of liquor and the number and locations of state-run liquor stores. It is possible, then, that in states where liquor sales are/were not as restrictive, there would be greater concentration of outlets as well as a broader geographic distribution that is driven by market and social forces. These factors could increase the likelihood that nearby availability of liquor outlets becomes situated in ways, which could, in turn, increase alcohol consumption among residents.

There are notable limitations to this study. First, identification of latent classes is sensitive to sample size. It is possible that with a larger number of neighborhood units, a greater number of distinct latent neighborhood classes would be observed. Another limitation is that one of the neighborhood indicators, neighborhood disorganization, was based on participants' self-report. Future research should explore more objective measures such as aggregation of reports from multiple residents in the neighborhoods who are not participants in the study from which individual outcome data are collected [26]. Finally, the use of cross-sectional data at a single developmental period is a limitation that prohibits determination of the temporal direction of the associations. However, we think that for the questions examined here, it is important that neighborhood measures are concurrent with measures of alcohol use because the neighborhood effect is hypothesized to be contemporaneous.

Conclusions

This study highlighted the use of a finite mixture modeling approach that can be used to identify distinct types of neighborhoods based on multiple neighborhood characteristics. This approach may hold promise for the

neighborhood effects research field. Further application of this method could inform public health practice with regard to identification of residential areas that may be most at risk for alcohol problems or other important population-health outcomes. In addition, understanding how unique combinations of neighborhood characteristics are associated with individuals' drinking could better inform research on the environmental mechanisms through which problem alcohol use arises and suggest targets for preventive strategies.

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