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Assessing Individuals' Exposure to Environmental Conditions Using Residence-Based Measures, Activity Location-Based Measures, and Activity Path-Based Measures

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Abstract

Background.—Many approaches are available to researchers who wish to measure individuals' exposure to environmental conditions. Different approaches may yield different estimates of associations with health outcomes. Taking adolescents' exposure to alcohol outlets as an example, we aimed to (i) compare exposure measures and (ii) assess whether exposure measures were differentially associated with alcohol consumption.

Methods.—We tracked 231 adolescents aged 14 to 16 years from the San Francisco Bay Area for four weeks in 2015/16 using GPS. Participants were texted ecologic momentary assessment surveys six times per week, including assessment of alcohol consumption. We used global positioning systems (GPS) data to calculate exposure to alcohol outlets using three approach types: residence-based (e.g. within the home census tract), activity location-based (e.g. within buffer distances of frequently attended places), and activity path-based (e.g. average outlets per hour within buffer distances of GPS route lines). Spearman correlations compared exposure measures, and separate Tobit models assessed associations with the proportion of ecologic momentary assessment responses positive for alcohol consumption.

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Results.—Measures were mostly strongly correlated within approach types (ρ≥0.7), but weakly (ρ<0.3) to moderately (0.3≤ρ<0.7) correlated between approach types. Associations with alcohol consumption were mostly inconsistent within and between approach types. Some of the residence-based measures (e.g. census tract: β=8.3, 95%CI=2.8–13.8), none of the activity location-based approaches, and most of the activity path-based approaches (e.g. outlet–hours per hour, 100m buffer: b=8.3, 95%CI=3.3–13.3) were associated with alcohol consumption.

Conclusions.—Methodologic decisions regarding measurement of exposure to environmental conditions may affect study results.

Keywords

Environment; weights and measures; surveys and questionnaires; geographic information systems; alcohol drinking; adolescent

Introduction

Ecologic studies emphasize that social and physical environmental conditions are associated with a wide range of health outcomes. For example, indices of social disadvantage are related to homicide in Chicago census tracts;[1] the closure of live poultry markets reduced poultry-to-person transmission of avian influenza A H7N9 virus in four Chinese cities;[2] radioactive iodine-131 dose predicted thyroid cancer incidence in Ukrainian and Belarussian settlements following the Chernobyl nuclear disaster.[3] Assessing whether population-level relationships such as these are observed at an individual level is an important step towards causal inference. Individual-level studies provide evidence against the ecologic fallacy (i.e. erroneously inferring individual-level associations from aggregated data)[4,5] and in support of causal mechanisms directly linking environmental conditions to health outcomes through the people who are exposed. Many approaches are available for researchers seeking to measure individuals' exposure to environmental conditions, and different approaches capture different aspects of this exposure. Nevertheless, it is not clear how the choices researchers make about how to measure exposure affects estimates of associations between environmental conditions and health outcomes.

Residence-Based Measures

The simplest approach to assessing individuals' exposure to environmental conditions is based on places of residence.[6,7] Where researchers know the street address or geographic coordinates of participants' homes, a common method is to use a Geographic Information System (GIS) to extend a buffer corresponding to a theoretically or empirically justified distance over which exposures might affect outcomes, then calculate exposure within the resultant polygon.[8,9] Spatial accessed-based measures also start with individuals' residential points, calculating exposure based on the aggregate distance to a set number of exposures (usually between 5 and 9).[10,11] Alternatively, actual point locations for homes may be unknown, but researchers can identify administrative units in which participants live (e.g. census tracts).[12,13]

Residence-based measures are very common because the requisite data are readily available, and environmental conditions proximate to the home may be theoretically relevant.[14]

However, several commentators point out that this approach can be critically limited because it does not account for exposure away from the home.[6,15–19] Identifying *activity spaces*, the set of places to which individuals travel as part of their routine activities, addresses this problem by allowing for more complete assessment of exposure.[20–24]

Activity Location-Based Measures

One approach to characterizing activity spaces is to identify the *activity locations* individuals frequent (e.g. workplace, school). These places can be identified by free-list[25,26], travel diary[27], guided interview[28], using geographic identifiers embedded in digital messages (e.g. Twitter[29]), or responses to text-based surveys.[30] Once activity locations are identified, many methods are available for constructing activity space polygons. Locations can be linked using a standard deviation ellipse,[27,31] a minimum bounding geometry[29] (e.g. a "convex hull"), or by connecting points using the shortest distance along the roadway network and calculating exposures within buffer distances around the resultant line.[32,33] Other approaches include taking circular buffers around activity locations, or selecting the administrative units in which the activity locations are situated.[34]

Using activity locations to approximate exposure to environmental conditions allows researchers to account for human mobility[35], potentially yielding important information about environmental exposures that occur away from the home. However, the approach requires that researchers interpolate or ignore exposures (and, often, activities) that occur between these specific points[36,37], and typically does not account for the time spent at each point. Moreover, many of these approaches also capture exposure at locations that individuals may not actually attend. For instance, a standard deviation ellipse includes places that individuals do not necessarily travel.[24]

Activity Path-Based Measures

Recent technological advances permit researchers to record individuals' *activity paths*, which are complete characterizations of a person's micro-geographic history over a given time. GIS-assisted interviews can be used to retrospectively construct digital representations of activity paths over brief periods (e.g. a single day).[38] Alternatively, global positioning systems (GPS) can record activity paths prospectively. While not appropriate for studies of rare outcomes, this approach eliminates recall bias regarding space–time locations and enables researchers to follow participants over longer periods than retrospective methods, and can also be paired with ecologic momentary assessments to provide additional contextual data.[34,39] There are many available methods for using GPS data to measure exposure to environmental conditions. Researchers have used GPS points to calculate exposures within raster cells[38], administrative units[40], circular buffers[41], standard deviation ellipses[42], or buffers around lines connecting sequential points.[39,43] Others have used algorithms to identify "staypoint" locations where participants are stationary for defined periods time, with exposures calculated at only these points.[44]

An activity path-based approach addresses key limitations of residence-based and activity location-based methods. The approach minimizes bias that arises due to human mobility and the need to approximate movement between activity locations. However, activity path-based measures are more susceptible to selective mobility bias, which is the concern that exposure to environmental conditions may predict health outcomes because the people who engage in the outcome behaviors choose to attend the exposure locations (i.e. reverse causation).[24,45,46] For example, fast food outlets may be related to energy intake because of deliberate trips to these outlets, not because individuals change their diet after they are exposed to outlets during routine activities.

Adolescents' Exposure to Alcohol Outlets

Adolescents' environmental exposure to alcohol outlets is an ideal example with which to examine the way different measures of individuals' exposure to environmental conditions relate to one another and to health outcomes. Ecologic studies provide some evidence that alcohol consumption is greater in areas with greater density of alcohol outlets,[47] and availability theory provides a link between the exposure and the outcome.[48] Adolescents are not of legal age to purchase alcohol in the US, minimizing (but not altogether eliminating) the likelihood that associations are due to selective mobility bias. Exposure to outlets may instead lead to easier indirect access to alcohol through family and social contacts due to reduced convenience costs associated with the initial purchase.[49–51] Alternatively, greater exposure could lead to perceptions of alcohol use as normative and could model use, leading to greater consumption.[19,52] Consistent with these theoretical mechanisms, some individual-level studies find alcohol consumption is related to residence-based measures of exposure to outlets, namely within administrative boundaries (e.g. cities[53]) and circular buffers around the home,[54–57] but others that use similar measures report null findings.[58] Different measurement approaches may explain these inconsistent results.

The aims of this paper are (i) to compare residence-based, activity location-based, and activity path-based measures of adolescents' exposure to alcohol outlets, and (ii) to assess whether these measures produce different estimates of the association with alcohol consumption. We hypothesized that different exposure measures would be poorly correlated with one another, and that the measures would be differentially associated with the outcome.

Methods

Data Collection

Healthy Communities for Teens is a longitudinal study of neighborhood contextual risks and alcohol, tobacco and other drug use and problem behaviors among adolescents. This analysis uses cross-sectional data for the first of three annual waves. A convenience sample of teens (n=261) was recruited from 10 mid-sized cities in the San Francisco Bay Area. These cities were the 10 closest to the Prevention Research Center (Oakland, CA) from among a random sample of 50 California cities with populations between 50,000 and 500,000. The Prevention Research Center has compiled detailed archival data from these 50 cities for a larger study of environmental prevention strategies to reduce alcohol-related harms.[59] The Healthy Communities for Teens sample was 41.6% male, and included 46 (18.0%) black, 52 (20.4%) Hispanic, and 177 (69.4%) white participants. Participants were recruited using a combination of online advertisements, paid peer referrals, posted flyers, phone recruitment, and outreach at community venues. Eligible teens (i) resided in one of the 10 study cities,

(ii) were aged 14 to 16 years between July 2015 and August 2016, (iii) had an active email address, and (iv) spoke English or Spanish. We obtained parental consent and teen assent prior to data collection, and the study protocol was approved by the Prevention Research Center's Institutional Review Board.

Wave 1 participants were provided with a GPS-enabled Apple iPhone 5c for one month between July 2015 and August 2016. We recorded participants' point locations (latitude, longitude), a date and time stamp every 60 seconds using ActSoft's Comet Smart Tracker (ActSoft Inc., Tampa, FL). Spatial data processing was performed using ArcGIS v10.3.[60]

Exposure Measures

We connected sequential GPS points by the shortest distance on a Euclidean plane, then deleted line segments that included locations outside California because we lacked contextual data for other states.[39,43] This approach produced a polyline for each participant, which is a path composed of one or more one dimensional segments. Polylines for this sample contained between 12,858 and 48,301 segments, and each segment included the date and time for the start- and end-points. The combination of all polyline segments for a participant represented their four-week activity path. Figure 1 shows the activity path for a single participant, depicted as a "space–time aquarium" in which increasing values on the z-axis represent time from baseline.[61,62]

Using 2013 data from the California Department of Alcoholic Beverage Control, we geocoded the locations of all alcohol outlets in the state with license type 23, 40, 42, 48, 61, and 75 (bars); 41 and 47 (restaurants); and 20 and 21 (off-premises outlets). We then assessed participants' exposure to alcohol outlets using measures based on (i) residential locations, (ii) activity locations, and (iii) activity paths using the procedures described below and depicted in Figure 2. Measures were calculated separately for bars, restaurants, off-premises outlets, and for all outlets combined.

Residence-Based Measures—The first group of measures was based on participants' places of residence. We geocoded the residential street addresses, and constructed circular buffers of 200m, 400m, 800m, and 1600m around these points. We then identified the census block groups and census tracts in which participants lived and calculated counts of outlets within these areas. Because the census polygons are not uniformly scaled we tested alternate constructions in which we denominated by land area for these administrative units. Finally, we measured spatial access as the sum of the inverse Euclidean (straight line) distances to the 5, 7, and 9 nearest outlets from the residence.

Activity Location-Based Measures—We used the GPS points to identify participants' activity locations, defined as the centroid of 200m buffered points where they spent a total of at least 60 minutes over at least 2 calendar days. We selected these parameters based on visual inspection of GPS data from a random sample of 10 participants. Activity locations were at least 400m apart from one another, and therefore the 200m buffers did not overlap (Figure 1). We calculated the total time that participants spent at each activity location, then constructed five different polygons for each participant: (i) 200m, 400m, 800m, and 1600m buffers around the activity locations, (ii) standard deviation ellipses, (iii) standard deviation ellipses weighted by the total time spent at each location, (iv) convex hulls, and (v) 50m, 100m, and 200m buffers around the shortest roadway network distance connecting all activity locations. We conducted sensitivity analyses using alternate constructions of the activity locations (i.e. points where participants spent at least 30 minutes). All associations were very similar compared to the main definition, so we report only that approach here.

Activity Path-Based Measures—We constructed five different activity path-based measures. First, we used 50m, 100m, and 200m buffers around the activity path polyline segments (approximating street segment width, street segment length, and line of sight, respectively[36]) then calculated aggregate counts of outlets within all polyline buffers along the activity path. Second, to account for different durations that participants were exposed to alcohol outlets, we weighted the total number of outlets within the polyline buffers by the duration of each corresponding polyline, then divided by the total time each participant was tracked, thereby calculating the average "outlet–hours" per hour of exposure participants accumulated along to their activity paths. By this approach, 2 outlets located within the buffer distance of a participant's static location (e.g. near their house) would contribute 2 outlet–hours per hour to the measured exposure (2 outlets × 60 minutes ÷ 60 minutes), whereas 2 outlets proximate to a single 60 second polyline segment (e.g. passed on a freeway while driving) would contribute a total of 0.03 outlet–hours (2 outlets × 1 minute ÷ 60 minutes). Third, we calculated outlet–hours for times that participants were more than 200m from home (in case time spent at home dominated the time-weighted measures). Fourth, we calculated the proportion of time participants were within the buffer distances of any outlet.[39] Finally, because previous GPS studies track participants for varying periods of time[38,40,43], we also calculated the outlet–hours measure using data collected over 2-weeks, 1-weeks and 1-day periods, beginning at 12am on the day after the participants began carrying the GPS units.

Outcomes

During the observation period, text messages were sent to the study smartphone six times per week from Thursday to Sunday with a link to an ecologic momentary assessment survey. The 1-minute surveys asked participants if they "had consumed any alcohol since the last text". Possible answers were "No", "Yes, since the last text", and "Yes, I'm doing this right now". We combined the two positive response categories to create a binary indicator for alcohol consumption between EMA surveys, then calculated the proportion of EMA responses positive for alcohol use.

Confounders

Many additional characteristics may confound associations between exposure to alcohol outlets and alcohol consumption. For example, adolescents who spend greater proportions of time away from home may have greater autonomy (e.g. less parental monitoring) and greater exposure to outlets, and less parental monitoring as associated with greater alcohol consumption.[63,64] We used the activity path data to calculate the proportion of time spent more than 200m from home. Similarly, to minimize the possibility that alcohol outlets are marking for greater geographic autonomy, we accessed geocoded point locations for all retail outlets from InfoUSA (Infogroup, Papillion, NE) and calculated the proportion of time participants were exposed to any retail outlets within 100m buffers of the activity path.

Alcohol outlet density is greater in disorganized and disadvantaged neighborhoods[65,66], and adolescents in such neighborhoods consume more alcohol.[39,67] Disorganization and disadvantage may therefore confound associations between exposure to alcohol outlets and alcohol consumption. Structural social characteristics are also associated with social disorganization within neighborhoods,[68,69] so socio-demographic characteristic are often used as proxies for disorganization.[70–72] We used 2015 American Community Survey 5-year estimates for census tracts to calculate the time-weighted average for an index of social disorganization: the sum of overall unemployment, households receiving public assistance, low income persons (< 100% poverty level), low income persons (100%–149% poverty level), high school dropouts, female-headed households, renter-occupied houses, and moved in the previous year (Cronbach's α=0.76).[39,73] We also identified the median household income for participants' residential census block groups.

Prior to the observation period, participants completed a 30-minute baseline survey that included assessment of sociodemographic characteristics and alcohol, tobacco, and other drug use. We identified participants' age (categorical), sex (dichotomous), race/ethnicity (categorical by Black, White, Hispanic, and other) and whether they reported ever consuming alcohol (binary).

Statistical Analysis

We discarded data for six participants for whom more than 99% of GPS points were within 200m of their home or whom we followed for fewer than 168 hours, and a further 24 participants who responded to fewer than three ecologic momentary assessment texts. Our final analytic sample was 231 participants.

To compare residence-based, activity location-based, and activity path-based measures of adolescents' exposure to alcohol outlets, we constructed a matrix of Spearman's rank order correlation coefficients. Separate matrices compared exposure to bars, licensed restaurants, off-premise outlets, and all outlets combined.

To assess whether these measures produce different estimates of the association with alcohol consumption, we constructed Tobit models for the proportion of ecologic momentary assessment responses in which participants indicated they had consumed alcohol.[74] Because 191 participants (82.7%) did not report any alcohol consumption in the ecologic momentary assessment responses, we accounted for censoring at a lower bound of zero. To enable comparison of effect sizes we standardized all exposure variables. Models controlled for age, sex, race/ethnicity, residential census block group income, exposure to all retail outlets, exposure to social disorganization, and the proportion of time spent away from home. Sensitivity analyses included alcohol consumption from the baseline survey, to limit the possibility of reverse causation. Further sensitivity analyses added random effects for city of origin, or used negative binomial models for counts of ecologic momentary assessment responses positive for alcohol consumption, with the total number of ecologic momentary assessment responses received as the offset. Results for all sensitivity analyses were substantively similar to the main analyses.

Results

The GPS software recorded a total of 9.1 million point locations. Table 1 provides summary statistics for participants' individual characteristics and exposure to all alcohol outlets within activity spaces. For brevity, the results presented in the main tables use buffer distances of 100m around line-based measures (e.g. activity paths, roadway distances) and 800m around point-based measures (e.g. activity locations, residences).

Table 2 shows Spearman correlation coefficients comparing the residence-based, activity location-based, and activity path-based measures of exposure to all alcohol outlets. Measures were generally moderately ($0.3 \leq \rho < 0.7$) to highly ($\rho \geq 0.7$) correlated within the different approach types. For example, among the residence-based measures, the sum of the inverse distances to the seven nearest outlets was very highly correlated with the 800m circular buffer ($\rho = 0.9$). The residence-based and activity location-based measures, and the residence-based and activity path-based measures were very poorly correlated with one another ($\rho < 0.3$). Correlations between the activity location-based and activity path-based measures were mostly moderate. Results were consistent across buffer sizes and outlet types (eTables 1 to 4).

Results of the Tobit models for the percent of EMA texts in which alcohol use was indicated are presented in full in eTable 5, and in reduced form in Table 3. Considering all alcohol outlets combined, none of the activity location-based measures were related to alcohol consumption; however, some of the residence-based exposure measures (e.g. census tract: $\beta = 8.3$, 95%CI=2.8–13.8) and most of the activity path-based measures were associated with the outcome (e.g. outlets per hour, 100m buffer: $\beta = 8.3$, 95%CI=3.3–13.3). The finding for census tracts indicates that a 1 standard deviation increase in the number of alcohol outlets within residential census tracts is associated with an 8.3-unit increase in the percent of EMA texts in which alcohol consumption is indicated, with a 95% confidence interval of 2.3 to 13.8. Findings were mostly inconsistent across polygon sizes for the residence-based measures. For example, outlet counts within 200m and 800m circular buffers and within census block groups and tracts were related to the outcome, but not within 400m or 1600m circular buffers or using the spatial access measure. Nevertheless, findings were mostly consistent across buffer sizes for the activity path-based measures and for different durations of data collection (i.e. 2-weeks, 1-week, 1-day). In general, exposure to bars and restaurants contributed most substantially to the association between all alcohol outlets and alcohol consumption. Effect sizes were strongest for exposure to bars using activity path-based measures.

Discussion

This study demonstrates that the approach taken to measuring individuals' exposure to environmental conditions can affect estimated relationships with health outcomes. Using adolescents' exposure to alcohol outlets as an example, we identified that residence-based, activity location-based, and activity path-based approaches produce highly varied exposure measures, and that estimated associations with alcohol consumption differed greatly across measurement approaches.

Implications for Studies of Exposure to Alcohol Outlets

Our findings may explain the inconsistent results in previous studies relating individuals' exposure to alcohol outlets to their own alcohol consumption.[47,58,75] Most previous studies use just one exposure measure, at best conducting sensitivity analyses at alternative geographic scales (e.g. residence-based measures using 1km and 3km buffers[55]). Had we not taken an expansive view of exposure to alcohol outlets, we may or may not have concluded that such exposure is associated with adolescents' alcohol consumption. Associations were strongest for activity path-based measures, suggesting greater space–time precision is important in this case.

Two complementary causal mechanisms explain how exposure to alcohol outlets would lead to greater alcohol consumption for adolescents who cannot legally purchase alcohol directly. First, alcohol will be more readily available through indirect means due to reduced convenience costs for of-age family and friends. Second, because adolescents' self-perceptions are closely and rigidly tied to their daily activities and social connections, and the neighborhoods they routinely encounter provide cues regarding behavioral norms[49,52,76], increased exposure to alcohol outlets will lead to perceptions of alcohol consumption as normative.[19,77] Our results provide stronger support for the normative behavior mechanism than the indirect access mechanism. Associations between exposure to alcohol outlets and alcohol consumption were more consistently positive for on-premises outlets (bars and restaurants) compared to off-premises outlets, and on-premises outlets are less likely to be a consistent indirect source of alcohol. Exposure to alcohol outlets may function as a form of alcohol advertising, encouraging adolescents to perceive alcohol consumption as normal and perhaps desirable, therefore contributing to increased consumption.

Implications for Studies of Exposure to Other Environmental Conditions

Our findings are highly relevant for individual-level studies of exposure to environmental conditions other than alcohol outlets. Space-time analysis relies on (often arbitrary) partitions of spatially and temporally structured data, and, as we demonstrate, the decision researchers make regarding these partitions can greatly affect study results. These judgments are most consequential when exposures vary over small geographic scales. For example, social disadvantage varies between city blocks in many urban settings,[36] and individual-level measures of exposure to this environmental condition will vary greatly, likely yielding different estimates of associations with outcomes (e.g. assault risks). In contrast, radioactive iodine-131 dose after the Chernobyl nuclear disaster varied over a wide geographic extent.[3] The different available approaches to measuring such exposure would be highly correlated within individuals, and effect estimates would therefore be very similar.

The theoretical mechanism linking the environmental exposure to the outcome will also determine the most appropriate measurement approach. Biological mechanisms (e.g. air pollution as a cause of asthma)[78] may require precise activity path data to most accurately characterize relationships, whereas social mechanisms (e.g. exposure to white neighborhoods as a source of stress for black adolescents due to unpredictability and diminished ontological security)[79] include the possibility that relationships are not dose-responsive, so complete space–time assessment may not be necessary.

Our data allow us to make one further important observation. The optimal duration to track study participants using GPS to construct activity spaces is not clear. Consistent with a recent suggestion[80], our results suggest the trade-off between efficiency and precision is greatest at approximately 2 weeks.

Limitations

The study sample and data collection methods for Healthy Communities for Teens lead to some important limitations. Most critically, although we minimized the potential for selective mobility bias because adolescents cannot legally access alcohol directly from the outlets to which they are exposed, it remains a possibility that some adolescents purchased alcohol directly, and that those who consume alcohol selectively attend areas with more alcohol outlets.[24,45,46] We are unable to establish the direction of this association with these cross-sectional data. Additionally, adolescents have less autonomy regarding their travel patterns than adults[81], and the extent to which results apply to adults are unclear. Very few respondents reported consuming alcohol, and it is possible that these small handful of people dominated the results of the multivariable models. We elected not to snap polyline segments to the roadway network, because the actual travel paths participants took between points was unknown. This error, as well as imprecision in GPS point locations, may have biased our results.[82] Nevertheless, associations between the exposure and the outcome was most consistently positive for the outlet–hours measures, and the impact of any error in the GPS points or polylines (e.g. impossibly transecting a city block) will add only a small amount of noise to these time-weighted measures.

Conclusions

Individual-level studies of exposure to environmental conditions and health outcomes are of critical importance if we to are understand the impact of social and physical environments on health. However, this area of research has considerable methodologic challenges. Because methodologic decisions can greatly affect study results, it is incumbent upon researchers to carefully select an approach to measuring geographic exposures. Rigorous sensitivity analyses will ensure that findings are not artefacts of selected measurement strategies. Similarly, we encourage readers to skeptically consider the impact that measurement approaches might have on reported associations.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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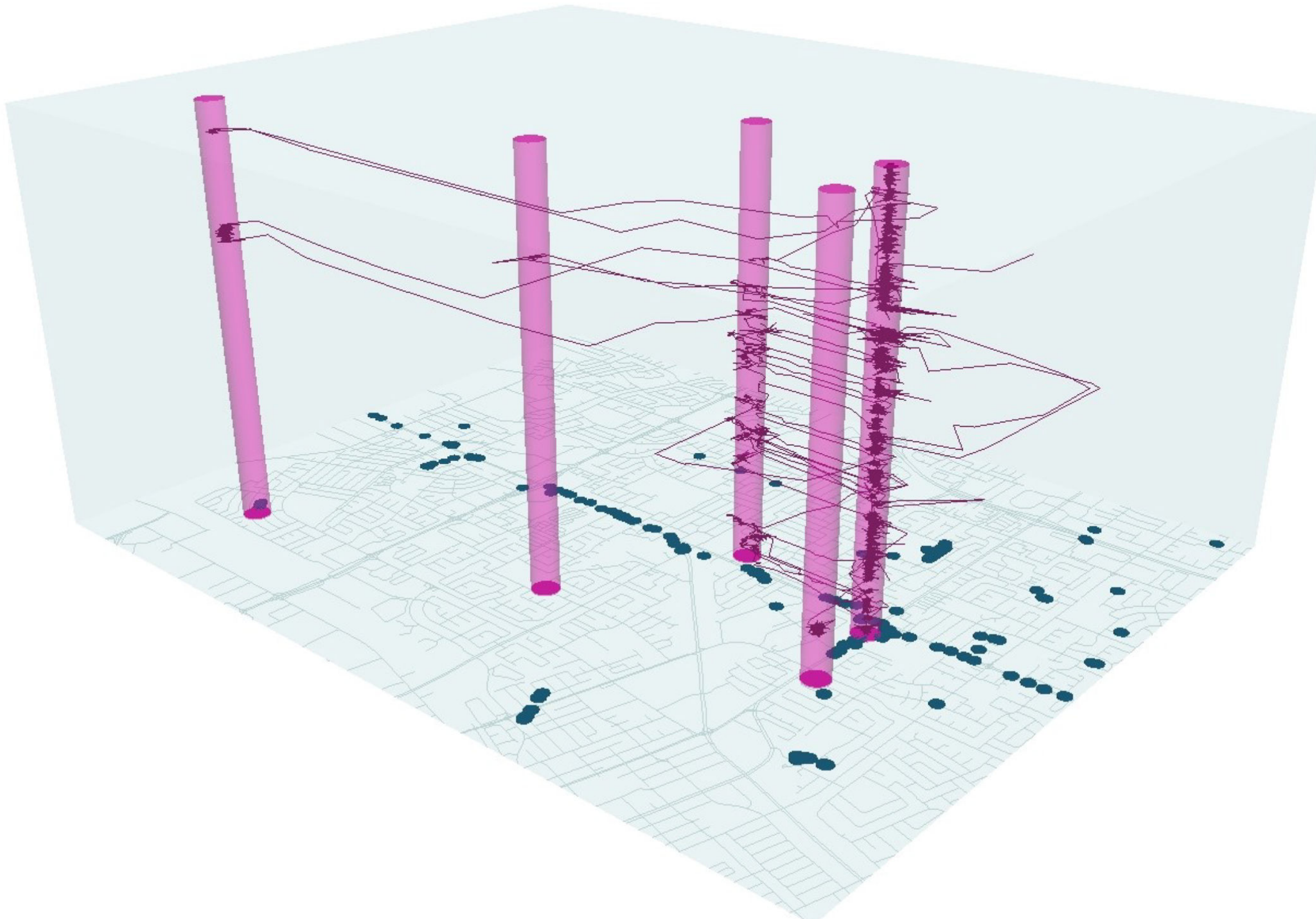

Figure 1.

Space-time aquarium, showing a four-week activity path for one participant. The z-axis represents time, the blue points are alcohol outlets, the continuous purple line is the participants' activity path, and the five purple columns are the five activity locations identified by search algorithm. Activity path and map features altered to protect participant confidentiality.

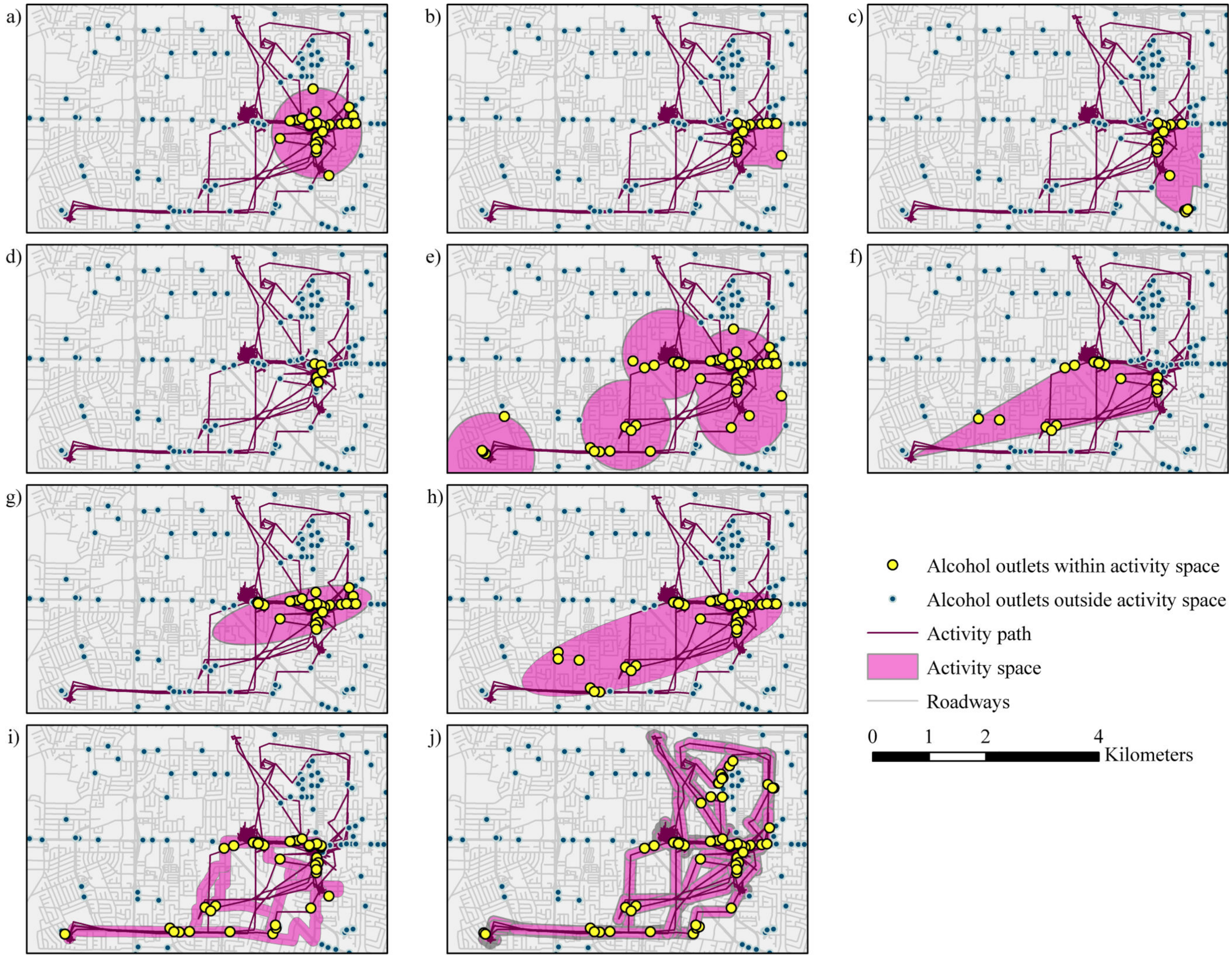

FIGURE 2.

Activity spaces and exposure to alcohol outlets as measured using **residence-based** measures: (A) circular buffer around residential location (800 m buffer), (B) residential census block group, (C) residential census tract, (D) seven closest outlets to residence by Euclidean distance; **activity location–based** measures: (E) circular buffers around activity locations (800 m buffers), (F) convex hull for activity locations, (G) standard deviation ellipse for activity locations (time-weighted), (H) standard deviation ellipse for activity locations (unweighted), (I) buffer around roadway network distance between activity locations (100 m buffer); and **activity path–based** measures: (J) GPS activity path data (100 m buffer). Activity path and map features altered to protect participant confidentiality.

Table 1.

Summary statistics for Healthy Communities for Teens Wave 1 data (n = 231)

	Mean	SD	Min	Max
Participant Characteristics				
Median household income (residential block group)	10.0	4.2	2.2	22.8
EMA responses	16.5	6.3	3.0	43.0
% EMA responses positive for alcohol consumption	3.1	9.7	0.0	66.7
GPS Data Collection				
GPS points collected	35640.2	6650.9	12858.0	45244.0
Time followed (hours)	604.3	110.5	215.1	764.4
% Time spent at home	69.0	14.4	13.0	97.5
Total distance (km)	1522.0	686.2	301.7	4612.2
Activity points	4.9	2.9	1.0	14.0
Polyline segment length (m)	42.8	184.5	0	7677.7
Residential Location Measures				
Circular buffer (800m)	9.4	14.7	0.0	99.0
Census block group (count)	3.6	6.4	0.0	47.0
Census tract (count)	11.2	14.5	0.0	87.0
Census block group (count per square km)	5.0	10.4	0.0	105.9
Census tract (count per square km)	4.5	6.9	0.0	63.7
Inverse distance weighted sum of 7 nearest outlets (Euclidean km)	15.5	14.5	1.7	117.2
Activity Location Measures				
Circular buffer (800m)	57.6	46.3	0.0	237.0
Convex hull	39.3	62.0	0.0	490.0
Standard deviation ellipse	62.4	81.3	0.0	669.0
Standard deviation ellipse (time-weighted)	16.2	36.0	0.0	254.0
Roadway network distance (100m buffer)	150.8	166.6	0.0	977.0
GPS-Based Measures				
Buffer around activity path line (100m buffer)	417.4	243.5	0.0	1265.0
Outlet–hours per hour (100m buffer)	0.3	0.6	0.0	5.5
Outlet–hours per hour - excluding home (100m buffer)	1.0	1.9	0.0	18.5
% Time exposed to any outlet (100m buffer)	9.6	18.2	0.0	95.8
Outlet–hours per hour - two week data (100m buffer)	0.3	0.6	0.0	5.7
Outlet–hours per hour - one week data (100m buffer)	0.3	0.7	0.0	5.9
Outlet–hours per hour - one day data (100m buffer)	0.3	0.6	0.0	6.3

EMA: Ecologic momentary assessment

Table 2.

Spearman correlation coefficients for activity path-based, activity location-based and residence-based measures of exposure to all alcohol outlets

[redacted]

Residential Location Measures																				
1	Circular buffer (800m)	1.00																		
2	Census block group (count)	0.34	1.00																	
3	Census tract (count)	0.40	0.52	1.00																
4	Census block group (count per square km)	0.48	0.92	0.46	1.00															0.9–1.0
5	Census tract (count per square km)	0.62	0.45	0.71	0.57	1.00														0.8–0.9
6	Inverse distance weighted sum of 7 nearest outlets (Euclidean km)	0.86	0.32	0.34	0.48	0.61	1.00													0.7–0.8
Activity Location Measures																				0.6–0.7
7	Circular buffer (800m)	0.21	0.17	0.23	0.10	0.10	0.15	1.00												0.5–0.6
8	Convex hull	0.06	−0.04	0.02	−0.09	−0.05	0.00	0.60	1.00											0.4–0.5
9	Standard deviation ellipse	0.11	−0.03	0.08	−0.07	0.00	0.05	0.57	0.93	1.00										0.3–0.4
10	Standard deviation ellipse (time-weighted)	0.29	0.14	0.24	0.12	0.19	0.29	0.44	0.66	0.67	1.00									0.2–0.3
11	Roadway network distance (100m buffer)	−0.01	−0.10	−0.07	−0.12	−0.01	0.02	0.31	0.39	0.35	0.30	1.00								0.1–0.2
Activity Path-Based Measures																				0–0.1
12	Buffer around activity path line (100m buffer)	−0.01	0.06	−0.02	0.04	0.05	0.04	0.18	0.20	0.16	0.20	0.57	1.00							< 0.0
13	Outlets per hour (100m buffer)	0.21	0.18	0.24	0.16	0.21	0.32	0.45	0.27	0.28	0.41	0.50	0.59	1.00						
14	Per hour – excluding home (100m buffer)	0.28	0.19	0.26	0.20	0.25	0.35	0.45	0.23	0.27	0.31	0.38	0.43	0.84	1.00					
15	% Time exposed to any outlet (100m buffer)	0.24	0.19	0.21	0.19	0.23	0.34	0.38	0.30	0.33	0.46	0.49	0.56	0.91	0.77	1.00				
16	Per hour – two-week data (100m buffer)	0.19	0.12	0.25	0.11	0.19	0.30	0.45	0.26	0.28	0.38	0.46	0.47	0.91	0.78	0.83	1.00			
17	Per hour – one-week data (100m buffer)	0.25	0.12	0.32	0.12	0.29	0.36	0.43	0.20	0.22	0.34	0.41	0.41	0.81	0.69	0.74	0.86	1.00		
18	Per hour – one-day data (100m buffer)	0.28	0.12	0.23	0.14	0.26	0.33	0.20	0.13	0.16	0.28	0.29	0.32	0.57	0.53	0.57	0.53	0.59	1.00	

Table 3.

Coefficients from Tobit models for the percent of EMA responses in which participants indicated any alcohol use (n = 231). All independent variables standardized. Models control for age, sex, race/ethnicity, the median household income for the residential Census block group, exposure to all retail outlets, exposure to neighborhood disorganization, proportion of time away from home.

	All Outlets			**Bars**			**Restaurants**			**Off Premise Outlets**		
	β	**(95%**	**CI)**	**β**	**(95%**	**CI)**	**β**	**(95%**	**CI)**	**β**	**(95%**	**CI)**
Residence-Based Measures												
Outlet count within circular buffer of residence (800m)	6.6	(0.6	12.6)	6.6	(1.5	11.7)	6.2	(0.0	12.4)	5.1	(−1.0	11.1)
Outlet count topithin Census block group	6.3	(0.6	11.9)	6.5	(1.6	11.4)	5.5	(−0.2	11.2)	5.2	(−0.8	11.2)
Outlet count topithin Census tract	8.3	(2.8	13.8)	8.3	(3.1	13.5)	6.4	(1.0	11.7)	7.9	(2.4	13.4)
Outlet density topithin Census block group (count per square km)	4.4	(−1.3	10.1)	5.8	(0.6	11.1)	3.5	(−2.3	9.4)	4.2	(−2.1	10.5)
Outlet density topithin Census tract (count per square km)	4.4	(−1.8	10.7)	4.6	(−1.3	10.4)	3.4	(−2.8	9.6)	4.7	(−1.7	11.2)
Inverse distance topeighted sum of 7 nearest outlets (km)	5.2	(−0.4	10.8)	5.5	(0.0	10.9)	5.1	(−0.1	10.3)	4.8	(−1.6	11.2)
Activity Location-Based Measures												
Outlet count topithin circular buffer around activity locations (800m)	4.3	(−2.2	10.8)	4.9	(−1.5	11.2)	2.7	(−4.2	9.5)	4.4	(−1.3	10.2)
Outlet count topithin convex hull	2.7	(−3.6	8.9)	2.5	(−3.7	8.7)	0.7	(−6.1	7.5)	4.2	(−1.5	9.9)
Outlet count topithin standard deviation ellipse	0.9	(−6.2	7.9)	-0.1	(−7.4	7.3)	-2.3	(−10.9	6.3)	3.5	(−2.6	9.6)
Outlet count topithin standard deviation ellipse (time-topeighted)	-0.5	(−7.9	6.8)	0.5	(−6.1	7.1)	-5.0	(−15.0	4.9)	2.4	(−3.4	8.2)
Outlet count along shortest roadtopay nettopork distance bettopeen activity locations (100m buffer)	0.8	(−5.9	7.4)	2.3	(−3.9	8.6)	-0.0	(−6.7	6.6)	1.7	(−5.0	8.4)
Activity Path-Based Measures												
Outlet count topithin buffer around activity path line (100m buffer)	5.4	(−1.9	12.6)	6.3	(−0.8	13.4)	4.2	(−2.8	11.2)	6.0	(−1.2	13.2)
Outlets per hour (100m buffer)	8.3	(3.3	13.2)	11.6	(4.5	18.7)	7.6	(3.3	11.9)	1.9	(−4.6	8.4)
Outlets per hour – excluding home (100m buffer)	7.7	(1.8	13.7)	12.4	(1.6	23.2)	6.3	(1.9	10.7)	1.2	(−6.9	9.3)
% Time exposed to any outlet (100m buffer)	4.4	(−1.7	10.4)	8.7	(3.1	14.3)	5.9	(0.7	11.0)	1.1	(−5.4	7.6)
Outlets per hour – ttopo-topeek data (100m buffer)	7.7	(2.8	12.6)	11.5	(3.8	19.1)	7.1	(2.9	11.4)	1.3	(−5.5	8.0)
Outlets per hour – one-topeek data (100m buffer)	7.9	(3.0	12.9)	11.8	(4.4	19.1)	7.4	(3.0	11.7)	1.2	(−5.7	8.0)
Outlets per hour – one-day data (100m buffer)	7.0	(2.2	11.8)		(4.9	19.0)	6.4	(2.1	10.8)	0.7	(−6.4	7.7)