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Real-Time Tracking of Neighborhood Surroundings and Mood in Urban Drug Misusers: Application of a New Method to Study Behavior in Its Geographical Context

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Abstract

Background—Maladaptive behaviors may be more fully understood and efficiently prevented by ambulatory tools that assess people's ongoing experience in the context of their environment.

Methods—To demonstrate new field-deployable methods for assessing mood and behavior as a function of neighborhood surroundings (Geographical Momentary Assessment; GMA), we collected time-stamped GPS data and Ecological Momentary Assessment (EMA) ratings of mood, stress, and drug craving over 16 weeks at randomly prompted times during the waking hours of opioid-dependent polydrug users receiving methadone maintenance. Locations of EMA entries and participants' travel tracks were calculated for the 12 hours before each EMA entry were mapped. Associations between subjective ratings and objective environmental ratings were evaluated at the whole neighborhood and 12-hour track levels.

Results—Participants (N=27) were compliant with GMA data collection; 3,711 randomly prompted EMA entries were matched to specific locations. At the neighborhood level, physical

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Contributors

D.H.E. helped design the study, performed the non-geographical statistical analyses, and wrote the first draft of the manuscript; M.T. and I.M.C. performed the geographical statistical analyses and wrote most of the accompanying methods in the manuscript; K.A.P. and M.L.J. helped design the study and oversaw clinical aspects of data collection; M.V., M.M., and J.-L.L., oversaw bioinformatic aspects of data collection; C.D.M.F.-H. oversaw the collection of the neighborhood-assessment data; K.L.P. conceived of the study, oversaw its design, and contributed heavily to the drafting of the manuscript. All authors discussed and commented on the manuscript.

Conflict of Interest

No conflict declared.

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disorder was negatively correlated with negative mood, stress, and heroin and cocaine craving ($ps < .0001$ to $.0335$); drug activity was negatively correlated with stress, heroin and cocaine craving ($ps .0009$ to $.0134$). Similar relationships were found for the environments around respondents' tracks in the 12 hours preceding EMA entries.

Conclusions—The results support the feasibility of GMA. The relationships between neighborhood characteristics and participants' reports were counterintuitive and counter-hypothesized, and challenge some assumptions about how ostensibly stressful environments are associated with lived experience and how such environments ultimately impair health. GMA methodology may have applications for development of individual- or neighborhood-level interventions.

Keywords

behavioral geography; activity space; ecological momentary assessment

1. INTRODUCTION

Many health problems can be conceptualized as having “biopsychosocial” origins or exacerbating components. Each part of that portmanteau—bio, psycho, social—describes a part of the problem more resistant to study than the preceding part. At the social level, ethnography provides data that are rich in experiential detail but are rarely suitable for aggregation and inferential statistics; epidemiology, just the reverse. Although neither approach permits strong causal conclusions, longitudinal epidemiological studies that control for impressively large arrays of individual-level factors suggest that behavioral and health-related outcomes may be determined as much by where one lives as by who one is (Stafford et al., 2010; Genberg et al., 2011). Direct evidence for a causal connection between place and outcome has been provided by a large randomized interventional study in which low-income adults who underwent residential relocation to lower-poverty neighborhoods showed reductions in extreme obesity and diabetes (Ludwig et al., 2011) and improvements in subjective well-being (Ludwig et al., 2012), compared to those who were not relocated. These findings call for more serious attention to modifiable determinants of mental and physical health that should not be dealt with solely at the level of individuals' traits and behaviors.

One limitation of most of the epidemiological studies, possibly accounting for some failures to find effects after neighborhood-level interventions (Goetz, 2010), is that “neighborhood” is treated as a static indicator corresponding to place of residence, ignoring the between- and within-person variability associated with daily movement through the environment (“activity space”; Kwan, 2009; Ledoux and Vojnovic, 2012). Differences in activity space can modify or suppress residential effects on health (Inagami et al., 2007; Vallee et al., 2011). Even when activity space is assessed, the assessment is typically retrospective and crude. To address this problem—which has been the focus of increasing concern from behavioral scientists (Richardson et al., 2013; Stahler et al., 2013)—we have developed and deployed methods to assess behavior, mood, and activity space in real time.

This study was an expansion of our prior work with ecological momentary assessment (EMA), in which we monitored behavior and mood in real time using handheld electronic devices that methadone-maintained outpatients carried daily for up to 20 weeks (Epstein et al., 2009). The new aspect of the current study was that participants also carried GPS loggers, resulting in time-stamped geographical data that could be matched to the EMA data in order to determine the environmental context (location) of the mood and behaviors study participants reported. We refer to this combination of EMA and GPS as “geographical momentary assessment” (GMA). In the present analyses, we evaluated GMA data in

relationship to environmental factors using an existing database of neighborhood ratings made by trained observers during the same year as our study (Furr-Holden et al., 2011).

Based on published findings using place of residence as a predictor (Stafford et al., 2010; Genberg et al., 2011; Ludwig et al., 2011, 2012), we hypothesized that momentary exposure to greater physical disorder, social disorder, and drug activity would be associated with momentary exacerbations of drug craving, stress, and negative mood. The basis for most of these predictions seems intuitively clear. For the more indirect associations—for example, physical and social disorder as predictors of drug craving—one could adduce findings that these types of neighborhood disorder have been associated with individuals' feelings of hopelessness (Mair et al., 2012), and that feelings of hopelessness may lead to seemingly self-destructive behaviors that bring short-term benefits (Tourigny, 1998). Physically or socially disordered neighborhoods might also induce drug craving in people who have a history of going to such neighborhoods to obtain drugs.

Here, however, we show that the relationships between location and mood were reliable but counterintuitive. We found these relationships when we used the characteristics of the whole neighborhood in which each mood rating was given, and also in separate analyses when we used the characteristics of the local environment around the participant's track in the hours preceding each mood rating.

2. METHOD

2.1 Participants

Participants were outpatients admitted for methadone maintenance at a research clinic in Baltimore, MD. Screening included medical, psychiatric, and drug-use histories, physical examination, standard laboratory tests, and a battery of assessment instruments, including the Addiction Severity Index (ASI; McLellan et al., 1985) and the Diagnostic Interview Schedule (DIS-IV; Robins et al., 1995). Eligibility criteria for enrollment were: aged 18 to 65, physical dependence on opioids, and evidence of cocaine and opiate use (self-report and urine). Exclusion criteria were: any DSM-IV psychotic disorder, history of bipolar disorder, or current major depressive disorder; current DSM-IV dependence on alcohol or sedative-hypnotics; cognitive impairment severe enough to preclude informed consent or valid self-report; and medical illness that would compromise participation.

The Institutional Review Board of the National Institute on Drug Abuse (NIDA) approved the study, and participants gave written informed consent before enrollment. All data were covered by a Federal Certificate of Confidentiality.

2.2 Standard treatment and drug-use monitoring

In this longitudinal cohort study, all participants received daily methadone and weekly individual counseling for up to 28 weeks, of which the last 8 weeks were a scheduled dose taper (before and during which, our clinic staff helped participants transfer to community methadone clinics). In weekly individual-counseling sessions, counselors completed a semistructured psychosocial assessment and treatment plan for each participant. Reduction of substance use was the primary goal. Methadone HCl (target dose 100 mg/day; Mallinckrodt, Inc., St. Louis, MO) was administered orally in cherry-flavored solution throughout the study. Abstinence reinforcement (vouchers given for urine specimens negative for cocaine, opiates, or both) was in place from weeks 7–18.

Participants attended clinic seven days a week except major holidays. Three times per week (usually Mondays, Wednesdays, and Fridays) urine specimens were collected under observation and tested by a commercial laboratory that gave qualitative results for cocaine

(benzoylecgonine equivalents; BZE), opiates (morphine), marijuana, and benzodiazepines (oxazepam). Cutoffs were 300 ng/ml for cocaine, opiates, and benzodiazepines, and 50 ng/ml for marijuana. Breath alcohol was determined with an Alco-Sensor III (Intoximeters, Inc., St. Louis, MO).

2.3 Procedures

We have reported other results from a similarly designed study using a different cohort and not incorporating GPS (Epstein et al., 2009); methodological details are summarized below.

2.3.1 EMA—At the end of week 3, each participant received a PalmPilot (PDA) that was programmed (Vahabzadeh et al., 2004) to emit three audible prompts per day at random times during the participant's typical waking hours. (Waking hours were set for each day of the week for each participant when the PDA was first issued, and they could be changed by study staff if the participant asked.) Participants used touchscreen buttons to respond to 5-point Likert-scale questions about drug cravings and stress and the presence or absence of 24 mood adjectives. Each entry also included a multiple-choice item about the respondent's current location (workplace, home, another's home, vehicle, etc.), enabling us to separate "at home" entries from "not at home" entries. Scores for "negative mood" and "positive mood" were derived from factor analyses of EMA ratings of the mood adjectives. Based on the factor loadings, "negative mood" was scored as the mean of 13 items (anxious, fatigued, worn out, afraid, annoyed, angry, hopeless, on edge, sad, discouraged, exhausted, bored, and uneasy) and positive mood was scored as the mean of eight items (carefree, in a good mood, happy, lively, cheerful, relaxed, contented, and pleased). The remaining three items (sleepy, vigorous, and resentful) did not load strongly on either factor and were not used¹.

2.3.2 GPS Data—Participants carried small, no-display GPS loggers (BT-Q1000X, Qstarz International). Devices were set to log geolocation (latitude, longitude, and altitude) every 20 meters or every 15 minutes, whichever came first. Participants were asked to carry the GPS unit with them at all times and to show it to staff at each clinic visit. Each week, GPS data were uploaded from the devices to our secure servers via USB. The data were visualized with the geographic information system (GIS) software ArcGIS (ESRI, Redlands, CA).

2.3.3 The Neighborhood Inventory for Environmental Typology (NifETy)—The NifETy is an observer-rated measure of physical and social disorder along a single blockface; it has been shown to have good interrater and internal consistency and criterion validity (Furr-Holden et al., 2010); for example, at the residential level, NifETy scores predict health and behavioral outcomes, at least in adolescents (Milam et al., 2012). We considered the NifETy particularly suitable for GMA because it reflects the blockface as experienced by a person passing nearby. The NifETy ratings were collected along 528 blockfaces in Baltimore during the same year our participants provided EMA data by trained raters under the supervision of a co-author (DFH) in a separately funded project².

2.4. Data analysis

Time and date stamps were used to link EMA random-prompt entries with GPS data. For visualization (not analysis), we created maps of EMA ratings of mood, craving, and stress using a standard geostatistical interpolation technique called ordinary kriging.

¹EMA mood-adjective factor loadings can be found in Table S1 in Supplementary Material by accessing the online version of this paper at <http://dx.doi.org> and by entering doi:...

²NifETy PCA loadings can be found in Table S2 in Supplementary Material by accessing the online version of this paper at <http://dx.doi.org> and by entering doi:...

The NIfETy items were dichotomous; to improve the distributional properties of the NIfETy data, we subjected them to principal-components analyses (PCA) within predefined categories including Social Disorder, Physical Disorder, and Drug Activity. The resultant PCA outputs were continuous values. NIfETy items were removed from the PCA analysis if they were never or very rarely observed. Each variable was treated as loading only on one component. We used only the first principal component from each of the three most theoretically relevant NIfETy categories: *Physical Disorder* (structures with broken windows; boarded abandoned buildings; unboarded abandoned buildings; vacant houses; vacant commercial buildings; unmaintained property; trash in street; trash in alley; trash in other open spaces; vacant lots; broken bottles; graffiti; damaged sidewalks; warning signs; bus stops; blue lights; days of the week posted for street cleaning; evidence of vandalism; absence of landscaping), *Social Disorder* (not perfectly quiet; people yelling; people swearing; people loitering; male adults loitering; male youth loitering; intoxicated people), and *Drug Activity* (drug paraphernalia; baggies; cotton swabs; rubber gloves; vials; blunt guts/wrappers; balloons; cigarette butts; mini-cigars; alcohol bottles). We created gridded surfaces of the NIfETy PCA scores using the ordinary kriging method.

Statistical analyses comparing EMA ratings and NIfETy data are described below. In all analyses, our criterion for significance was .05, two-tailed.

2.4.1 Neighborhood-level analyses—For neighborhood-level analyses, we used ArcGIS to aggregate the original NIfETy data, GPS, and EMA data within the established boundaries of each of 55 BNIA neighborhoods (Baltimore Neighborhood Indicators Alliance, 2012; BNIA). Each EMA rating was analyzed in terms of averaged NIfETy ratings for social disorder, physical disorder, and drug activity in the entire neighborhood in which it had occurred. We analyzed only the EMA entries in which participants reported their location as being anywhere other than “home” because we were interested in the effects of transient exposures to different types of environments. We used general linear mixed models (SAS Proc Mixed) to account for autocorrelation in the data. Each model included one time-varying predictor (the neighborhood’s score on the NIfETy variable of interest) and one person-level predictor (the number of EMA data points each participant had contributed to the analysis, to help control for unequal numbers of assessments). The predictors were treated as fixed, and a first-order autoregressive error structure was used. The dependent measure (i.e., the unit of observation) was individual EMA reports, nested within participants.

2.4.2 Track-level analyses—We used ArcGIS to intersect GPS points with data from each of the three gridded NIfETy surfaces (Physical Disorder, Social Disorder, and Drug Activity), creating three NIfETy measures per point.

Track-level analyses were conducted to determine whether the associations in the neighborhood-level analyses would hold up under a different set of assumptions about both time and space. Space, in these analyses, was a string of single points that were used to sample pixels (each 90m by 90m) from the NIfETy gridded data; the points represented the tracks covered by the participant prior to the EMA entry—corresponding more closely to what the participant had actually experienced. Time was the 12 hours leading up to the entry, divided into 30-minute increments. Each GPS point along the track was assigned the kriged NIfETy value of the pixel in which it fit. The average number of seconds before and after each GPS point was used as a multiplier for the environmental exposure measure at each point, so that the relative exposure per point was time sensitive.

The Proc Mixed models for the track-level analyses were similar to the models for the neighborhood-level analyses, with track PCA scores as time-varying predictors (and each

participant's number of EMA data points as a person-level predictor). We had no *a priori* information about the duration of track that would be most strongly associated with a subsequent EMA rating; presumably this would vary across instances, but would also have some optimal value in the aggregated data. Therefore, we tested models using increasing amounts of track data in 30-minute increments: 30, 60, 90, and so on up to 12 hours.

3. RESULTS

3.1. Participant Characteristics and EMA and GPA compliance

Demographic characteristics and urine drug screen results during the study are shown in Table 1.

The 27 participants completed a total of 7,222 EMA entries; 894 were event-contingent reports of drug use or craving episodes (not used in these analyses), and 6,328 were random-prompt entries. Compliance to random prompting was good: participants responded to a mean of 79.0% (SEM 3.7; median, 85%) of issued prompts. We collected 11,390,403 raw GPS points, covering roughly 50,800 hours. Raw GPS points per participant ranged from 1,828,522 (approximately 1,976 hours) to 16,906 (approximately 324 hours).

3.2. Mapped self-report and neighborhood measures

We were able to match 5,434 random-prompt entries to GPS points, but 1,723 of these were discarded because they were not located in Baltimore City and therefore could not be matched to NifETy data. Figure 1 shows participants' momentary ratings of heroin craving, negative mood, stress, cocaine craving, and positive mood mapped onto the city of Baltimore. Across the maps, red indicates less desirable ratings (greater craving, stress, or negative mood, or less positive mood).

Figure 2 shows the observer-rated NifETy scores for Drug Activity, Social Disorder, and Physical Disorder; again, red always indicates less desirable ratings. Table 2 shows prevalences of individual indicators, such as broken windows, at blockfaces with specific ranges of Physical Disorder scores to provide a more concrete sense of the levels of disorder shown on the map.

3.3 Neighborhood-level analyses

As suggested by the maps in Figures 1 and 2 and supported by general linear mixed models (SAS Proc Mixed; Table 1), neighborhood analysis results were consistently opposite to our hypotheses. Greater social disorder in the neighborhood was associated with *lower* momentary ratings of cocaine craving. Greater physical disorder in the neighborhood was associated with *lower* momentary ratings of cocaine craving, heroin craving, negative mood, and stress. More drug activity in the neighborhood was associated with *lower* momentary ratings of cocaine craving, heroin craving, and stress. Even the associations that were not statistically significant were almost always in a direction opposing our hypotheses, as can be seen in the beta values.

3.4 Track-level analyses

Because mood and craving may be influenced not only by the environment experienced at the moment of reporting, but also by the environments experienced in the preceding hours, we examined the track traveled 12 hours prior to each random-prompt entry. The results (Figure 3) were consistent with the counterintuitive results from the neighborhood-level analyses and were more robust. Associations for heroin craving, negative mood, and stress were strongest in models using 4.5 to 5 hours of track data, suggesting that this was the relevant time scale for environmental influences on ratings. The association between cocaine

craving and the three NifETy scales in the track data were significant at all time points, but the slope (b) of the relationship was shallow and did not change with cumulative time before the prompt. The directions of the relationships between positive mood and the NifETy scales were opposite to those of negative mood but did not reach statistical significance at any cumulative time.

4. DISCUSSION

The results were unexpected in several ways, one of which seems easy to reconcile with prior data. We found high ratings of stress and negative mood as our participants moved through neighborhoods that, to the naked eye of external raters, appeared to have few indicators of violence, physical decay, or drug activity. Perhaps this was a momentary-level manifestation of an effect that has been documented in longer-term studies: feelings of exclusion in unwelcoming social settings (Schofield et al., 2011; Goosby and Walsemann, 2012).

The other unexpected aspect of our results—low ratings of stress and negative mood in neighborhoods that were more highly disordered—is more at odds with both common wisdom and prior data. A large body of research at the residential level has shown that exposure to impoverished or disordered neighborhoods is a strong predictor of adverse health outcomes (Stafford et al., 2010), adverse behavioral outcomes (Furr-Holden et al., 2011; Genberg et al., 2011; Turrell et al., 2012), and biological markers of chronic stress (King et al., 2011). Indeed, the Baltimore neighborhoods in which we found low ratings of stress are the neighborhoods with the lowest life expectancies in the city (Baltimore Neighborhood Indicators Alliance). What could reconcile the long-term findings with our momentary findings? One possible interpretation is suggested by a recent fMRI study showing that urban dwellers, compared to non-urban dwellers, had greater amygdala reactivity to acute stress in the absence of any difference in subjectively experienced stress (Lederbogen et al., 2011). That finding, combined with ours, suggests that some deleterious effects of neighborhood deprivation and disorder could occur outside conscious awareness. An anonymous reviewer suggested, and we agree, that we should not assume that what appears disorderly to an outside observer will feel stressful to someone in his or her own neighborhood. What our raters scored as loitering, swearing, or yelling might really have been friends having a good time together. A rich body of literature on “humanistic geography” emphasizes the idea that any given place can be experienced in very different ways by different people (Tuan, 1974). Even so, we still have to explain a large body of well-controlled epidemiological work suggesting that living in disorderly neighborhood is physically and psychologically stressful in the long run.

The possibility of important mental events that cannot be self-reported does not reduce the value of the EMA component of GMA. EMA has challenged common assumptions by showing, in well-powered studies, the absence or smallness of expected correlations, as between negative mood and smoking in most smokers (Shiffman et al., 2002) or between weather and mood in most people (Watson, 2000). The handheld devices used for EMA can also administer neuropsychological tasks, and performance on one such task during drug-craving episodes predicted latency to relapse (Marhe et al., 2013).

We had expected the predictive value of the track-level exposures to fall off rapidly in the hours preceding EMA entries. Our reasoning was that stress, mood, or craving at a given entry might be affected by minutes or hours of immediately preceding experience, but that this would be highly heterogeneous across occasions, and the heterogeneity would become too great after the first hour or two. This was partly borne out, especially for negative mood and to a lesser degree for stress, but we were surprised to see that the full 12 hours of track-

level exposure was often predictive of heroin craving. This finding may be useful in future work in which environmental exposure is used to predict increase risk of relapse vulnerability and the need for intervention, perhaps delivered through the same mobile electronic device capturing the data.

The main limitation of the study is the sample size, which precluded controlling for trait-level predictors or for current drug use. However, the mixed models accounted for repeated measures, making it less likely that the results were skewed by individual participants. The fact that the unexpected associations occurred all over the city increases our confidence in their not being an artifact of a few anomalous events. We have also manually examined our raw EMA data and found nothing in participants' reported activities and "fill in the blank" responses that readily accounted for the high levels of stress in seemingly less risky neighborhoods.

The associations we found were not large, with effect sizes equivalent to Pearson r values of .05 to .19. However, the pattern was clear and consistent. We consider this an instance of what some biostatisticians call "small effects that tell a big story": detection of a reliable signal under inauspicious testing conditions (Prentice and Miller, 1992; Cortina and Landis, 2009). A larger sample is likely to address the issue of effect size: with power to include person-level predictors and additional momentary predictors (e.g., current activity), we can account for more of the variance in mood, craving and stress, and we can test the predictive value of location over and above those other variables. (Another level of predictor we did not attempt to test was that of the individual neighborhood itself—e.g., whether being in Fells Point, Baltimore is associated with different patterns of behavior than being in Canton, Baltimore, in ways that are not reducible to any of our quantifiable measures, but are instead associated with the unique identities of the specific neighborhoods. The only way to address this statistically would be to collect a large number of observations from multiple participants within each of the 55 neighborhoods. In the current data set, the unique effects of specific neighborhoods are simply part of the error variance. If GMA were to be used as a real-time intervention that predicted individuals' imminent risks, we might address unique neighborhood effects with a future-predicting model that weights prior EMA reports from within the neighborhood more heavily than EMA reports from merely similar neighborhoods.) We wish to emphasize the feasibility of the GMA methodology. Our current results require replication, but the convergence of results from our two analytic approaches bolsters confidence in them.

Finally, although we specifically studied polydrug users, our goal is for GMA to be useful for studying environmental influences on behavioral health in general. We first developed GMA as part of an NIH initiative to improve environmental assessment for studies of gene/environment interactions, but GMA is not limited to use in observational designs. Incorporated into randomized interventional studies (with interventions either at the individual or neighborhood level), GMA could be both a measure of implementation fidelity and a measure of outcome. Ambitious past attempts at neighborhood interventions have been criticized for overlooking crucial aspects of relationships between environment and experience (Clampet-Lundquist and Massey, 2008; Goetz, 2010). Our initial findings suggest that those relationships may be even more complex than is often assumed, underscoring the need for rigorous, sensitive measurement to precede and accompany interventions.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Fig. 1. Participants' EMA ratings of heroin craving, stress, negative mood, cocaine craving, and positive mood ($N = 3,711$ random-prompt responses). Black dots show locations where individual EMA ratings were made; color coding shows kriged interpolations of the ratings. Red represents higher ratings for all measures except positive mood (blue represents higher ratings).

Fig. 2.

Trained observers' NifETy ratings of neighborhood characteristics of 528 blockfaces in Baltimore. Black dots show locations where ratings were made; color coding shows kriged interpolations of the ratings. Red consistently indicates less desirable ratings.

Fig. 3.

Relationships of craving, mood, or stress with track-level environmental exposures, using various amounts of track data. Each track was a string of single pixels (each 90m by 90m) from the NIfETy gridded data, representing GPS data from the participant preceding an EMA rating. Each data point in the graphs is a nonstandardized regression coefficient (with its associated standard error) from a Proc Mixed model; its sign reflects the direction of the association. Filled symbols indicate significant differences from 0 ($p < .05$, two-tailed). All statistically significant associations were counter to the hypothesized direction. The number of data points contributing to each coefficient ranges from 613 to 1,603, with the median number being 776.

Table 1**Participant Characteristics and Drug Use**

N	27 participants
Women	41%
African American	41%
Age	41.2 years (<i>SD</i> = 7.7, range 21–55)
Education	11.3 years of (<i>SD</i> = 2.0, range 7–16),
Employment	Unemployed 26%; Part time 33%; Full time 37%; Student 4%
Marital status	Never married 56%; Separated or divorced 33%; Married 11%
Income per month	Legal \$506 (<i>SD</i> = 574)
	Illegal \$251 (<i>SD</i> = 445)
Heroin	Route (N = 27) injected intravenously 48%, insufflated 52%
	Lifetime use 14.4 years (<i>SD</i> = 7.3, range 3–27)
	Use in past 30 days 25.7 days (<i>SD</i> = 8.5, range 0–30)
Other Opioids	Route (N = 15) oral 100%
	Lifetime use 1.0 years (<i>SD</i> = 2.7, range 0–10)
	Use in past 30 days 1.7 days (<i>SD</i> = 3.0, range 0–10)
Cocaine	Route (N = 19) smoked 68%, intravenous 11%, insufflated 21%.
	Lifetime use 5.6 years (<i>SD</i> = 7.3, range 0–21)
	Use in past 30 days 2.1 days (<i>SD</i> = 4.1, range 0–15)
Cannabis	
	Lifetime use 6.4 years (<i>SD</i> = 7.7, range 0–26)
	Use in past 30 days 1.2 days (<i>SD</i> = 2.2, range 0–8)
Urine-detected drug use during study	
	Opiate positive 31% (<i>SD</i> 29, range 0–90%)
	Cocaine positive 17% (<i>SD</i> 26, range 0–95%)
	Cannabis positive 16% (<i>SD</i> 30, range 0–65%)
	Benzodiazepine positive 14% (<i>SD</i> 29, range 0–97%)

Table 2

Illustrations of specific NifETy indicators by ranges of PCA scores.

NifETy Measure	NifETy PCA Index Scale for Physical Disorder*					
	1	>1 to 2	>2 to 3	>3 to 4	>4 to 5	>5
N of blockfaces in PCA Index Scale range	123	77	93	69	69	97
Structures with Broken Windows	0%	3%	5%	7%	19%	60%
Boarded Abandoned Buildings	1%	3%	11%	23%	41%	85%
Unboarded Abandoned Buildings	0%	1%	3%	9%	14%	31%
Vacant Houses	12%	17%	26%	26%	49%	55%
Vacant Commercial Buildings	0%	0%	2%	6%	13%	25%
Unmaintained Property	3%	17%	24%	54%	77%	88%
Trash in Street	8%	58%	87%	91%	96%	98%
Trash in Alley	0%	6%	12%	29%	28%	48%
Trash in Other Open Spaces	4%	62%	76%	93%	93%	96%
Vacant Lots	2%	5%	9%	9%	17%	39%
Broken Bottles	8%	26%	58%	65%	78%	88%
Graffiti	1%	16%	39%	55%	78%	94%
Damaged Sidewalks	30%	40%	55%	83%	83%	88%
Warning Signs	48%	61%	69%	59%	74%	87%
Bus Stops	8%	23%	37%	26%	45%	52%
Blue Light(s) Present	0%	0%	4%	4%	14%	31%
Days of Week Posted for Street Cleaning	2%	8%	15%	26%	22%	47%
Evidence of Vandalism	0%	6%	2%	17%	17%	33%
Evidence of Landscaping [inverse]	99%	99%	99%	91%	87%	68%

Values indicate the percent of times the specific NifETy measure was present in scores across the range of PCA index scale scores.

Table 3

Associations between whole-neighborhood NifETy characteristics and EMA ratings.

EMA item	NifETy Scale		
	Social Disorder	Physical Disorder	Drug Activity
Cocaine Craving	b = $-.06 \pm .02$, p = .0081*	b = $-.04 \pm .01$, p = .0002*	b = $-.05 \pm .01$, p = .0009*
Heroin Craving	b = $-.07 \pm .04$, p = .08	b = $-.08 \pm .02$, p < .0001*	b = $-.09 \pm .03$, p = .0003*
Negative Mood	b = $.02 \pm .02$, p = .39	b = $-.02 \pm .01$, p = .0335*	b = $-.009 \pm .01$, p = .48
Positive Mood	b = $-.04 \pm .02$, p = .08	b = $.01 \pm .01$, p = .21	b = $.009 \pm .02$, p = .56
Stress	b = $-.05 \pm .04$, p = .19	b = $-.05 \pm .02$, p = .0072*	b = $-.06 \pm .03$, p = .0134*

Note. Beta values are nonstandardized regression coefficients from Proc Mixed models; the signs reflect the direction of the association. In all instances, the associations were counter to the hypothesized direction.