



Published in final edited form as:

Drug Alcohol Depend. 2025 December 01; 277: 112927. doi:10.1016/j.drugalcdep.2025.112927.

Trajectories of neighborhood-level overdose risk predictions for prioritization of harm reduction services: Results from the PROVIDENT study

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Abstract

Background: Neighborhood-level overdose risk may vary over time. In Rhode Island, we developed and validated a machine learning model to identify the 20 percent of census block groups (CBGs) at the highest predicted risk of future overdose death. We updated this model periodically between November 2021 and August 2024 to generate six sets of predictions. This study aims to characterize the trajectory of each CBG's predicted overdose risk over time across these six periods.

Methods: In each prediction period, CBGs were designated as "high risk" or not designated as "high risk" based on our model's 20 percent predicted overdose risk threshold. We implemented sequence analysis to describe unique trajectories in each CBG's risk designation over each prediction period. We then calculated optimal matching distances to estimate dissimilarity between each pair of trajectories and applied agglomerative hierarchical clustering to group similar trajectories.

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Results: The 809 CBGs included in this study followed 60 unique trajectories in predicted overdose risk designation over the six prediction periods. Clustering of trajectories favored a solution with five trajectory groups. Most CBGs (73.4 %) were rarely or never designated as “high risk”, 7.9 % of CBGs were always designated as “high risk”, and the remaining 18.7 % were designated as “high risk” in multiple prediction periods, represented by trajectory groups with different patterning over time.

Conclusions: Given the substantial variability in which CBGs were at highest overdose risk over time, dynamic machine learning predictions may inform harm reduction resource allocation by identifying neighborhoods with emerging needs.

Keywords

Drug overdose; Harm reduction; Machine learning; Predictive analytics; Sequence analysis

1. Introduction

Drug overdose remains a leading cause of death in the United States. In 2022, nearly 110,000 people died due to a drug overdose, representing an increase of almost 150 % in the age-adjusted rate of drug overdose deaths over the past decade (Spencer et al., 2025). These accelerations in drug-related harms have been attributed to an increasingly toxic illicit drug supply, with the introduction of highly potent adulterants such as fentanyl and xylazine (Jones et al., 2018; Alexander et al., 2022). The ongoing criminalization, stigmatization, and dehumanization of people who use drugs inhibits access to adequate resources and supports needed for healthy living, including naloxone and other harm reduction supplies (Bratberg et al., 2023). In addition, limited federal and state funding for harm reduction programs has historically resulted in low coverage of these services in the United States, and presents additional challenges for community-based organizations to reach the substantial number of people at risk for fatal overdose (Cohen et al., 2022; Skinner et al., 2024a). Finally, rapid changes in the unregulated drug supply in the US over the last two decades have increased the number of people at risk for drug overdose, placing increased demand on limited harm reduction services.

These factors contribute to an overdose crisis that reflects a combination of entrenched structural vulnerability with acute risk due to volatility in the drug supply or disruptions to local harm reduction service provision. As such, fatal overdose burden can vary substantially within jurisdictions. In Rhode Island, for example, rates of death due to drug overdose between 2016 and 2020 ranged from 15.5 deaths to 46.9 deaths per 100,000 residents across its 240 census tracts (Cartus et al., 2023). In the context of limited resources and substantial geographic variation in overdose deaths, harm reduction services ought to be directed to neighborhoods at highest risk. Despite several studies that have identified a range of community-level characteristics associated with higher rates of drug overdose deaths (Cartus et al., 2023; Skinner et al., 2024b), few studies have identified longer-term patterns in neighborhood-level overdose susceptibility over time. In addition, overdose surveillance information is often monitored at a municipality, county, or region level, and may be lagged by several months, limiting its ability to inform timely resource allocation. Importantly, with sparsity in overdose events at small geographic resolutions and significant reporting

delays of drug overdose deaths in public health surveillance systems, novel forecasting tools, including those leveraging advances in machine learning for neighborhood-level prediction, may have utility in informing the rapid delivery of harm reduction resources to specific communities where they are most needed (Schell et al., 2022; Allen et al., 2023).

While several studies have reported on the potential application of machine learning for prediction of drug-related harms at the individual level to inform clinical practice (Lo-Ciganic et al., 2019, 2022; Gellad et al., 2023), studies that have applied and evaluated these approaches at the community level are rare. In November 2021, our team launched PROVIDENT (PReventing Overdose using Information and Data from the EnvironmeNT), a randomized trial that seeks to assess the utility of a machine learning model to predict neighborhood-level rates of drug overdose deaths in guiding the allocation and delivery of harm reduction resources across Rhode Island neighborhoods (Marshall et al., 2022). The present study aims to apply techniques of sequence analysis to identify neighborhood-level trajectories in predicted overdose susceptibility over the trial period. In doing so, we hope to distinguish neighborhoods that were persistently versus sporadically (or never) predicted by the PROVIDENT model to be at high risk of elevated overdose mortality over time, as a means of informing tailored harm reduction interventions in these neighborhoods.

2. Methods

2.1. Study setting

PROVIDENT is a randomized community intervention trial that aims to assess the effectiveness of proactive allocation of limited harm reduction resources based on machine learning predictions. Working in close collaboration with the Rhode Island Department of Health (RIDOH), our multi-institutional academic team leveraged a range of data sources to develop and validate a machine learning model, capable of identifying the top 20 percent of census block groups (CBGs) across Rhode Island that would contain at least 40 % of statewide overdose deaths in the subsequent six months. The development and validation of this predictive model has been described previously (Schell et al., 2022; Allen et al., 2024). In brief, our ensemble machine learning model produced fatal overdose predictions in six-month intervals, using over 200 CBG-level time-varying predictors including overdose mortality, emergency medical services-attended nonfatal opioid overdose, Prescription Drug Monitoring Program patient and prescription information, American Community Survey (ACS) demographic characteristics (with yearly updates to the rolling five-year averages), and publicly available land use, health care, and social service availability. These predictions were then made available to harm reduction outreach staff via an online platform integrated into the state's existing drug overdose surveillance dashboard (Allen et al., 2024). This dashboard also provided CBG-level information to partnering community organizations about community composition and social vulnerability indicators, as well as designated points of interest based on high foot traffic. Dashboard users from partnering community organizations were trained and encouraged to submit assessment and planning surveys that were embedded in the dashboard to allocate harm reduction resources to neighborhoods at highest risk of future overdose death. Prior studies have shown varying degrees of organizational engagement with the model predictions, although staff generally found

this information to have face validity and to supplement other available sources of data (Skinner et al., 2025; Krieger et al., 2025; Gray et al., 2025). In addition to detecting neighborhoods with emerging overdose risks, predictions were often used to reinforce longstanding outreach efforts in high-burden areas.

We updated the machine learning model and interactive dashboard approximately biannually between the PROVIDENT trial launch and its end date in August 2024, generating six sets of CBG-level predictions—released in November 2021, June 2022, November 2022, July 2023, December 2023, and July 2024. Across each prediction period, CBGs could fluctuate between being designated by the model as “high risk” and not designated as “high risk” according to the top 20 percent predicted overdose risk threshold. The PROVIDENT study has previously been described in further detail, and received ethical approval from RIDOH and Brown University (Marshall et al., 2022; Allen et al., 2024).

2.2. Data analysis

To characterize CBG-level patterns in predicted overdose risk designations over each prediction period, we conducted sequence analysis. For each of the six prediction periods, we first classified each inhabited CBG in Rhode Island ($N = 809$) into one of two potential states: designated as “high risk” and not designated as “high risk.” In doing so, we constructed a unique trajectory of predicted overdose risk designations over time for each CBG, allowing for a potential 64 unique trajectories (2 states^6 prediction periods). We then calculated optimal matching distances between every pair of unique trajectories to estimate the “cost” of transforming one unique trajectory into another (Halpin, 2010). Using these optimal matching distances, we applied agglomerative hierarchical clustering to assign each unique trajectory to a group of similar trajectories (Abbott and Tsay, 2000). This approach initially considers all unique trajectories to be distinct trajectory groups, and then clusters similar trajectory groups together until only one trajectory group remains (Ward, 1963). To determine the optimal number of trajectory groups, we used a majority rule based on 30 cluster-stopping indices available in the NbClust (Version 3.0.1) package (Charrad et al., 2014). With each neighborhood assigned to a trajectory group, we then reported cumulative rates of non-fatal overdose during the trial period, as documented by emergency medical services runs in response to suspected overdoses and made available for research purposes by the Rhode Island Emergency Medical Services Information System. We also described the demographic and socioeconomic conditions of each trajectory group using data from the United States Census Bureau’s ACS (5-year estimates, 2015–2019). All analyses were conducted in R (Version 4.2.1) using the tidyverse (Version 2.0.0), tidycensus (Version 1.4.1), TraMineR (Version 2.2.7), cluster (Version 2.1.4), and NbClust (Version 3.0.01) packages.

3. Results

Among 809 CBGs, there were 60 observed unique trajectories (out of 64 possible combinations) in overdose risk designations over the six prediction periods. Among these unique trajectories, clustering of trajectories favored a solution with five trajectory groups.

As presented by Fig. 1 and Supplementary Figure 1, these five trajectory groups correspond to CBGs that were designated as “high risk”:

Group 1: Rarely or never (73.4 %, $n = 594$)

Group 2: With decreasing likelihood (4.2 %, $n = 34$)

Group 3: With increasing likelihood (5.7 %, $n = 46$)

Group 4: Often (8.8 %, $n = 71$)

Group 5: Always (7.9 %, $n = 64$)

Neighborhoods in trajectory groups that were more frequently predicted to be at high risk of elevated overdose mortality over time also had higher rates of non-fatal overdose during the trial period, relative to those in trajectory groups that were more sporadically predicted to be at high future fatal overdose risk (Table 1). The trajectory groups also largely followed a racialized socioeconomic gradient, with CBGs in groups defined by more consistent designations as “high risk” throughout the trial period having fewer white residents and poorer socioeconomic circumstances than those defined by less consistent or no designation as “high risk” (Table 1). Relative to CBGs that were rarely or never designated as “high risk,” residents of neighborhoods that were always designated as “high risk” were 3.16 times more likely to be Black (11.1 % vs. 3.5 %) and 4.96 times more likely to be Hispanic or Latino (37.8 % vs. 7.6 %). Residents and households in neighborhoods that were always designated as “high risk” were also 3.65 times more likely to report incomes below the federal poverty line (26.0 % vs. 7.1 %), 2.61 times more likely to be without health insurance coverage (8.1 % vs. 3.1 %), 4.33 times more likely to receive cash public assistance (37.2 % vs. 8.6 %), and 2.76 times more likely to be paying more than 30 % of their incomes towards housing costs (32.2 % vs. 11.7 %), compared to neighborhoods that were rarely or never designated as “high risk.”

4. Discussion

By identifying the trajectory groups that emerged from fatal overdose forecasting over six prediction periods, we found that a majority (81.3 %) of neighborhoods were consistently designated as either “high risk” or not “high risk” over the trial period. Specifically, the PROVIDENT machine learning model consistently designated 7.9 % of neighborhoods as “high risk” and 73.4 % of neighborhoods were consistently not designated to be at “high risk.” The three trajectory groups that comprised the remaining 18.7 % of neighborhoods were largely differentiated by non-fatal overdose burden, racial and ethnic composition, and socioeconomic need. Our results align with previous research that found that overdose hotspot neighborhoods were characterized by higher proportions of Black and Latino residents, unemployment, and cost-burdened households (Samuels et al., 2024). While structural vulnerability predisposes certain communities to elevated overdose risk, retrospective hotspot analyses only capture past events. Sequences of PROVIDENT model predictions add value to existing data sources by capturing the underlying trajectories of risk, providing foresight into emerging patterns. This information allows policymakers and

public health practitioners to design effective, long-term solutions for neighborhoods that remained consistently at “high risk” over time, and to plan for scaling intervention capacity as areas are newly identified as “high risk”.

Our findings highlight a cluster of 7.9 % of neighborhoods in Rhode Island that were consistently designated as “high risk” for future overdose deaths and likely require the most focused allocation and delivery of harm reduction resources. Structural supports, including affordable housing, economic opportunity, and racial justice efforts, are additionally necessary to address the elevated fatal overdose burden in these neighborhoods that remain “high risk” over time (Bratberg et al., 2023; Skinner et al., 2024b; Park et al., 2020; Goedel et al., 2019; Wu and Evangelist, 2022; Milaney et al., 2021; Austin et al., 2021; Pamplin et al., 2023). Additionally, these neighborhoods demonstrate a need for fixed-site harm reduction resources, such as overdose prevention centers, syringe services programs, and access to voluntary substance use disorder treatment.

Although these high-risk neighborhoods may be familiar to local community-based harm reduction organizations, predictive tools like the PROVIDENT machine learning model could be most useful for identifying the 18.7 % of neighborhoods with variable prioritization status over time. Distinguishing between the three trajectory groups that were at moderately high risk over time (as identified by our data-driven approach to clustering) may be less meaningful from an intervention standpoint (i.e., for allocating harm reduction resources). Neighborhoods across each of these “middle” trajectory groups likely also require structural intervention, paired with dynamic direction of harm reduction resources and supports for people who use drugs. Notably, the emerging at-risk neighborhoods (i.e., the 5.7 % of neighborhoods with increasing likelihood of designation as “high risk” over the trial period) were often located in urban jurisdictions, and may benefit from city-level interventions.

Finally, the 73.4 % of neighborhoods that were consistently designated as not “high risk” still experience a non-zero risk of future overdose mortality and require baseline supports with close monitoring to identify increases in overdose burden. For instance, efforts to increase access to community-based and over-the-counter naloxone available in pharmacies may help to prevent fatal overdoses in all municipalities.

Although the PROVIDENT predictive model has been previously validated and exceeded its performance targets, the findings of the present study must be considered in the context of the model’s potential limitations. First, the model’s validity is not necessarily consistent for all CBGs. Additionally, uncertainty in ACS measures (a key source of model predictors) is greatest for small subgroups in small geographic units such as CBGs (Wei et al., 2023). It is possible that these ACS data-related issues with sampling error and measurement error could be better addressed using census tract estimates (Wei et al., 2023; Arribas-Bel et al., 2016), but CBGs were preferred by the intended audience of the PROVIDENT model results (i.e., community harm reduction organization staff) as a more actionable geographic unit for guiding resource allocation (Allen et al., 2024). Throughout the trial period, we held several trainings with our partner community organizations to make outreach staff aware of the limitations of the model and to help guide what they may and may not infer from its predictions. In particular, we noted that predicting overdose risk at small spatial units (e.g.,

census block groups) may be prone to error resulting from uncertainty in ACS measures, among other factors.

Nonetheless, future research should examine the relative validity of overdose prediction trajectories at the CBG versus census tract level. Methods that account for uncertainty in ACS measures in small subgroups remain under development (Wei et al., 2023), and innovative methods that can improve area-based prediction modeling to account for CBG-level error variance remain highly important. Alternatively, methods for retrospective analysis of data by space and time (e.g., local indicators of spatial associations, spatial scan statistics) could be used for identifying areas historically at high risk of overdose and for targeting interventions. Future research could apply a similar analytic approach to the present study to create trajectories based on whether CBGs were identified as “overdose hotspots” over time, which may produce different patterns than our findings that were based on predictions. Spatial machine learning approaches (Shaamala et al., 2025) for predicting overdose hotspots (such as those using long short-term memory networks) also offer a potential avenue for further investigation. In particular, deep learning methods (designed to handle long-term dependencies in sequential data) have been successfully used to predict flood risk dynamically over time (Zhou et al., 2023). Similar to flood risk, overdose is highly variable across space and time, requires many inputs to predict accurately, and, as a result, can be quite computationally intensive. Future research should investigate the feasibility of these methods for predicting neighborhood-level overdose risk.

Our results are limited to the Rhode Island context, but provide preliminary evidence that machine learning predictions may inform overdose prevention resource allocation by identifying neighborhoods that are both emerging hotspots of overdose risk and those consistently predicted to be at high risk of elevated overdose mortality.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Author disclosures

This work was supported in part by the National Institute on Drug Abuse (R01DA046620). Bennett Allen reports additional financial support provided by the Centers for Disease Control and Prevention (K01CE003586). These funding sources had no involvement in the conceptualization or writing of this manuscript nor the decision to submit for publication. The authors declare no further competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Brandon Marshall reports financial support was provided by National Institute on Drug Abuse. Bennett Allen reports financial support was provided by Centers for Disease Control and Prevention. All other authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:[10.1016/j.drugalcdep.2025.112927](https://doi.org/10.1016/j.drugalcdep.2025.112927).

References

- Abbott A, Tsay A, 2000. Sequence analysis and optimal matching methods in sociology: Review and prospect. *Socio Methods Res* 29 (1), 3–33.
- Alexander RS, Canver BR, Sue KL, Morford KL, 2022. Xylazine and overdoses: Trends, concerns, and recommendations. *Am. J. Public Health* 112 (8), 1212–1216. [PubMed: 35830662]
- Allen B, Neill DB, Schell RC, et al. , 2023. Translating predictive analytics for public health practice: A case study of overdose prevention in Rhode Island. *Am. J. Epidemiol* 192 (10), 1659–1668. [PubMed: 37204178]
- Allen B, Schell RC, Jent VA, et al. , 2024. PROVIDENT: Development and validation of a machine learning model to predict neighborhood-level overdose risk in Rhode Island. *Epidemiol* 35 (2), 232.
- Folch DC, Arribas-Bel D, Koschinsky J, Spielman SE, 2016. Spatial variation in the quality of American Community Survey estimates. *Demography* 53 (5), 1535–1554. [PubMed: 27541024]
- Austin AE, Shiue KY, Naumann RB, Figgatt MC, Gest C, Shanahan ME, 2021. Associations of housing stress with later substance use outcomes: A systematic review. *Addict. Behav* 123, 107076. [PubMed: 34385075]
- Bratberg JP, Simmons A, Arya V, Bhatia A, Vakharia SP, 2023. Support, don't punish: Drug decriminalization is harm reduction. *J. Am. Pharm. Assoc* 63 (1), 224–229.
- Cartus AR, Goedel WC, Jent VA, et al. , 2023. Neighborhood-level association between release from incarceration and fatal overdose, Rhode Island, 2016–2020. *Drug Alcohol Depend* 247, 109867. [PubMed: 37084507]
- Charrad M, Ghazzali N, Boiteau V, Niknafs A, 2014. NbClust: An r package for determining the relevant number of clusters in a data set. *J. Stat. Softw* 61, 1–36.
- Cohen A, Vakharia SP, Netherland J, Frederique K, 2022. How the war on drugs impacts social determinants of health beyond the criminal legal system. *Ann. Med* 54 (1), 2024–2038. [PubMed: 35852299]
- Gellad WF, Yang Q, Adamson KM, et al. , 2023. Development and validation of an overdose risk prediction tool using prescription drug monitoring program data. *Drug Alcohol Depend* 246, 109856. [PubMed: 37001323]
- Goedel WC, Green TC, Viner-Brown S, Rich JD, Marshall BDL, 2019. Increased overdose mortality during the first week of the month: Revisiting the “check effect” through a spatial lens. *Drug Alcohol Depend* 197, 49–55. [PubMed: 30776571]
- Gray JY, Krieger M, Skinner A, et al. , 2025. “Sometimes I’m interested in seeing a fuller story to tell with numbers” Implementing a forecasting dashboard for harm reduction and overdose prevention: A qualitative assessment. *BMC Public Health* 25 (1), 915. [PubMed: 40055691]
- Halpin B, 2010. Optimal matching analysis and life-course data: The importance of duration. *Socio Methods Res* 38 (3), 365–388.
- Jones CM, Einstein EB, Compton WM, 2018. Changes in synthetic opioid involvement in drug overdose deaths in the United States, 2010–2016. *JAMA* 319 (17), 1819–1921. [PubMed: 29715347]
- Krieger M, Yedinak J, Duong E, et al. , 2025. An overdose forecasting dashboard for local harm-reduction response. *Health Promot Pr.* 10.1177/15248399251335620.
- Lo-Ciganic WH, Donohue JM, Yang Q, et al. , 2022. Developing and validating a machine-learning algorithm to predict opioid overdose in medicaid beneficiaries in two US states: A prognostic modelling study. *Lancet Digit Health* 4 (6), e455–e465. [PubMed: 35623798]
- Lo-Ciganic WH, Huang JL, Zhang HH, et al. , 2019. Evaluation of machine-learning algorithms for predicting opioid overdose risk among Medicare beneficiaries with opioid prescriptions. *JAMA Netw. Open* 2 (3), e190968. [PubMed: 30901048]
- Marshall BDL, Alexander-Scott N, Yedinak JL, et al. , 2022. Preventing overdose using information and data from the environment (PROVIDENT): Protocol for a randomized, population-based, community intervention trial. *Addiction* 117 (4), 1152–1162. [PubMed: 34729851]
- Milaney K, Passi J, Zaretsky L, et al. , 2021. Drug use, homelessness and health: Responding to the opioid overdose crisis with housing and harm reduction services. *Harm Reduct. J* 18 (1), 92. [PubMed: 34446034]

- Pamplin JR, Rouhani S, Davis CS, King C, Townsend TN, 2023. Persistent criminalization and structural racism in US drug policy: The case of overdose Good Samaritan laws. *Am. J. Public Health* 113 (S1), S43–S48. [PubMed: 36696623]
- Park JN, Rouhani S, Beletsky L, Vincent L, Saloner B, Sherman SG, 2020. Situating the continuum of overdose risk in the social determinants of health: A new conceptual framework. *Milbank Q* 98 (3), 700–746. [PubMed: 32808709]
- Samuels EA, Goedel WC, Jent V, et al. , 2024. Characterizing opioid overdose hotspots for place-based overdose prevention and treatment interventions: A geospatial analysis of rhode island, USA. *Int. J. Drug Policy* 125, 104322. [PubMed: 38245914]
- Schell RC, Allen B, Goedel WC, et al. , 2022. Identifying predictors of opioid overdose death at a neighborhood level with machine learning. *Am. J. Epidemiol* 191 (3), 526–533. [PubMed: 35020782]
- Shaamala A, Yigitcanlar T, Nili A, Nyandega D, 2025. Machine learning applications for urban geospatial analysis: A review of urban and environmental studies. *Cities* 165, 106139.
- Skinner A, Li Y, Jent V, et al. , 2024b. Spatiotemporal analysis of the association between residential eviction and fatal overdose in Rhode Island. *BMJ Public Health* 2 (1), e000756. [PubMed: 40018241]
- Skinner A, Neill DB, Allen B, et al. , 2025. Assessing user engagement with an interactive mapping dashboard for overdose prevention informed by predictive modeling in Rhode Island. *J. Public Health Manag Pr* 10.1097/PHH.0000000000002200.
- Skinner A, Nolen S, Cerdá M, Rich JD, Marshall BDL, 2024a. A simple heuristic for allocating opioid settlement funding to reduce overdose mortality in the United States. *Am. J. Drug Alcohol Abus* 50 (3), 269–275.
- Spencer MR, Garnett MF, Miniño AM, 2024. Drug overdose deaths in the United States, 2002–2022. In: *National Center for Health Statistics Data Brief No. 491 Centers for Disease Control and Prevention, Hyattsville, MD.* 10.15620/cdc:135849.
- Ward JH, 1963. Hierarchical grouping to optimize an objective function. *J. Am. Stat. Assoc* 58 (301), 236–244.
- Wei R, Knaap E, Rey S, 2023. American Community Survey (ACS) data uncertainty and the analysis of segregation dynamics. *Popul Res Policy Rev* 42 (5).
- Wu P, Evangelist M, 2022. Unemployment insurance and opioid overdose mortality in the United States. *Demography* 59 (2), 485–509. [PubMed: 35212718]
- Zhou Q, Teng S, Situ Z, et al. , 2023. A deep-learning-technique-based data-driven model for accurate and rapid flood predictions in temporal and spatial dimensions. *Hydrol. Earth Syst. Sci* 27 (9), 1791–1808.

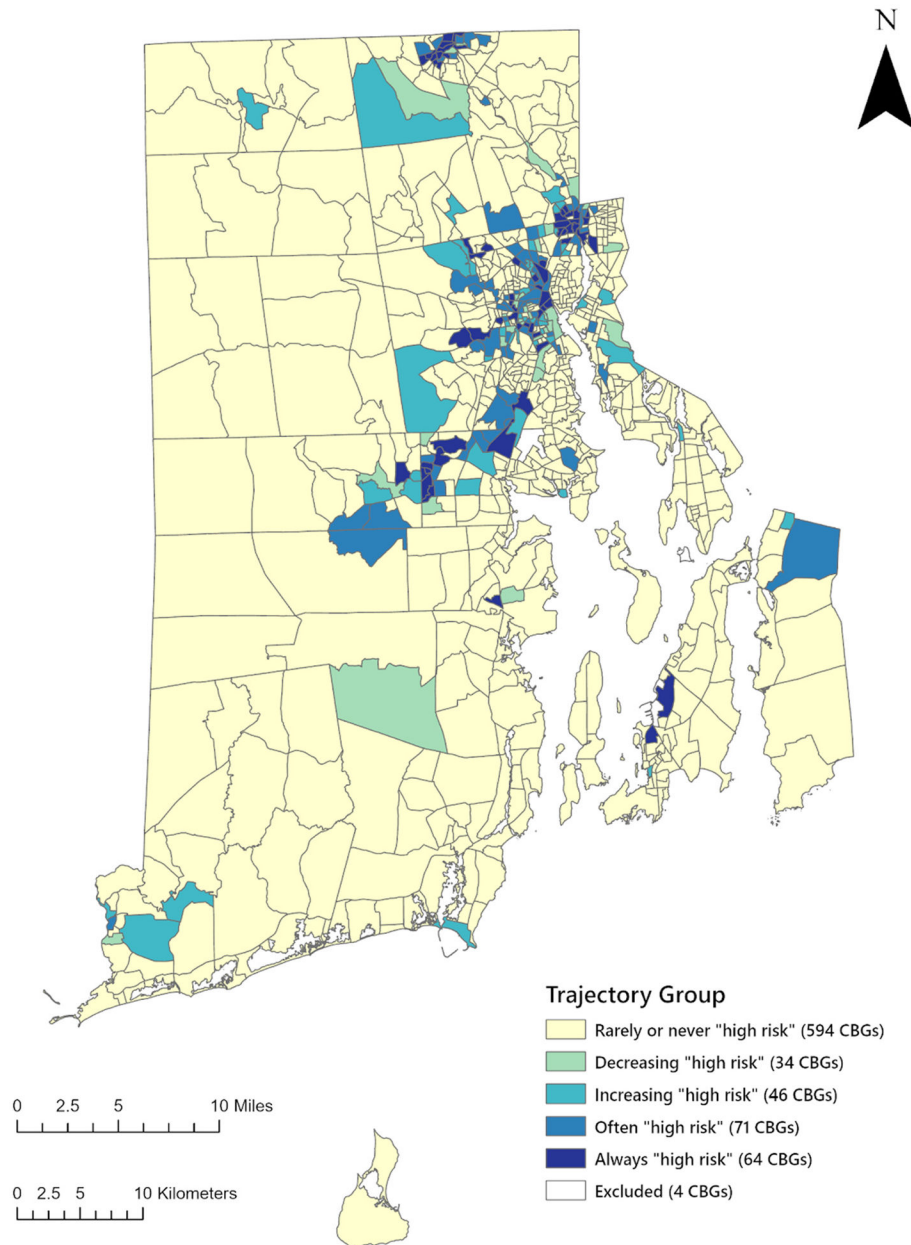


Fig. 1.

Map of Rhode Island census block groups by trajectory group. The figure presents a map of Rhode Island, with each census block group shaded according to its corresponding trajectory group. Trajectory groups were defined by clusters of census block groups in Rhode Island that followed similar trajectories of fatal overdose risk designation over six iterations of machine learning predictions during a 34-month trial period between November 2021 and August 2024.

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Table 1
Census block group-level distributions of non-fatal overdose and socioeconomic characteristics by trajectory group^a.

Characteristic	Rarely or never “high risk” Median (interquartile range)	Increasing “high risk” likelihood	Decreasing “high risk” likelihood	Often “high risk”	Always “high risk”
Non-fatal overdose rate per 100,000	6.7 (2.8 – 11.5)	13.2 (9.6 – 21.1)	16.9 (7.5 – 31.7)	16.8 (10.7 – 31.7)	23.5 (14.9 – 45.4)
Race, % Black	0.5 (0.0 – 4.7)	3.9 (0.0 – 10.3)	9.0 (0.9 – 13.4)	8.3 (3.1 – 15.8)	9.4 (2.6 – 16.6)
Race, % white	88.0 (73.0 – 94.5)	70.2 (23.3 – 89.6)	47.7 (34.4 – 79.6)	48.5 (23.4 – 72.9)	36.0 (19.3 – 64.0)
Ethnicity, % Hispanic or Latino	3.8 (0.6 – 11.2)	13.4 (2.6 – 42.6)	24.6 (13.2 – 55.1)	25.1 (9.9 – 52.2)	30.6 (11.0 – 53.7)
Population living at or below federal poverty line, %	5.7 (2.3 – 11.9)	15.8 (8.3 – 25.0)	24.8 (13.2 – 29.3)	16.7 (9.2 – 27.9)	26.8 (16.3 – 34.4)
Population receiving public assistance, %	0.0 (0.0 – 3.9)	3.9 (0.0 – 8.7)	5.4 (1.7 – 11.7)	5.7 (1.4 – 11.3)	7.1 (3.5 – 12.8)
Unemployment rate, %	3.5 (1.0 – 6.5)	5.1 (3.3 – 8.2)	7.7 (3.0 – 13.4)	5.3 (2.4 – 14.2)	8.4 (4.0 – 12.9)
Cost-burdened households ^b , %	17.0 (0.0 – 31.0)	18.9 (9.6 – 29.0)	19.0 (13.0 – 29.3)	26.8 (12.3 – 37.0)	23.1 (17.5 – 31.4)
Severely cost-burdened households ^c , %	16.2 (0.0 – 30.9)	20.0 (9.5 – 37.8)	24.0 (19.8 – 30.1)	19.0 (13.0 – 24.5)	20.7 (13.1 – 26.7)

^aTrajectory groups were defined by clusters of census block groups in Rhode Island that followed similar trajectories of fatal overdose risk designation over six iterations of machine learning predictions during a 34-month trial period between November 2021 and August 2024

^bHouseholds are considered cost-burdened when they spend more than 30 % of their income on rent, mortgage payments, and other housing costs.

^cHouseholds are considered severely cost-burdened when they spend more than 50 % of their income on rent, mortgage payments, and other housing costs.