Simulating Mobile MOUD Clinics and Targeted Overdose Prevention for Opioid Use Disorder in Massachusetts: A Simplified Markov Model Inspired by RESPOND

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Introduction

The opioid crisis remains one of the most critical public health emergencies in the United States, with opioid use disorder (OUD) contributing to a steady increase in overdose deaths over the past two decades.[1] OUD is a chronic, relapsing condition characterized by cycles of compulsive opioid use, withdrawal, frequent relapse, and a high risk of fatal overdose. The ongoing opioid epidemic has led to a record number of drug overdose deaths, making it one of the most urgent and complex public health challenges in recent United States history.[2] Although medications for OUD (MOUD), such as buprenorphine and methadone, are known to be effective, real-world access to these treatments is limited. Many people are unable to start treatment in a timely manner or stay in treatment for long due to regulatory barriers, shortages of qualified providers, social stigma, insufficient transportation, and structural inequities in healthcare.[1,3] These challenges are especially pronounced in high-risk groups, including people who are homeless or otherwise socially disadvantaged, and in "treatment deserts," where specialty addiction services are scarce or absent, further limiting access to evidence-based care.[4]

Given this context, Massachusetts, like many other states, has been deeply affected by the opioid epidemic. Public health efforts have increasingly focused on expanding MOUD coverage, improving retention in treatment, and targeting high-risk periods when the risk of fatal overdose is highest. These periods include the time immediately following release from jail or after residential detoxification. Individuals recently released from incarceration face a dramatically elevated risk of opioid overdose mortality, especially within the first two weeks after release, when loss of tolerance and disruptions in care greatly increase the risk of fatal overdose.[5]

However, implementing these strategies remains challenging due to service gaps, difficulties engaging high-risk individuals, and a lack of integrated support systems to prevent relapse and promote long-term recovery.[3] Notably, community-based mobile MOUD clinics and telehealth services are now being used to improve access in underserved areas, and interventions such as initiating MOUD prior to release from jail or detox are being explored to reduce preventable overdose deaths during these critical periods. Mobile health clinics have been shown to meet a wide range of health and social needs among people experiencing homelessness by providing care directly in their living environments and overcoming traditional barriers to healthcare access. These clinics deliver timely, person-centered care and foster greater engagement with the healthcare system.[6]

Given the complexity and urgency of these challenges, simulation modeling provides a valuable tool for evaluating the potential public health impact of alternative strategies before they are implemented on a large scale. In response to these needs, this project develops a simplified Markov model inspired by the RESPOND framework to simulate weekly transitions among key health and treatment states for individuals with OUD in Massachusetts. By modeling the effects of expanded mobile MOUD clinics and targeted overdose prevention strategies, this study aims to generate insights that can inform and improve decision making in public health policy and resource allocation.

Methods

RESPOND Model Structure

The Researching Effective Strategies to Prevent Opioid Death (RESPOND) model is a state-transition, cohort-based simulation developed to evaluate the population-level effects of interventions for opioid use disorder (OUD) in Massachusetts. RESPOND is designed to capture the dynamic, relapsing-remitting nature of OUD by simulating weekly transitions among health states such as active opioid use (injection and non-injection), non-active use (injection and non-injection), treatment engagement (e.g., buprenorphine, methadone, naltrexone), post-treatment vulnerability, overdose, and death (Figures 2 and 3).[7, 8]

Model inputs and parameters are highly customizable, allowing users to adapt the simulation to different populations, treatment settings, and intervention strategies. Key parameters include demographic and clinical characteristics of the initial cohort, transition probabilities between drug use and treatment states, overdose and mortality risks, and new OUD incidence rates. These parameters are estimated using multiple data sources, such as the Massachusetts Public Health Data Repository, national clinical trials, and published medical literature.[7, 8]

The core simulation operates on a weekly time cycle to reflect the short-term dynamics of treatment episodes, relapse, and overdose risk. RESPOND can simulate either a closed cohort or an open cohort with ongoing incident cases. The model produces projections for a range of outcomes, including all-cause mortality, overdose deaths, and treatment engagement, supporting both system-level evaluation and policy decision-making.[7, 8]

Simplified Markov Model Structure

Despite its strengths, the RESPOND model's complexity and data requirements can pose challenges for conducting rapid, targeted simulation studies. Therefore, this project constructs a simplified Markov model inspired by RESPOND’s structure and logic, but adapted for greater transparency and flexibility. The model simulates weekly transitions across a reduced set of key health and treatment states to evaluate the impact of expanding mobile MOUD clinics and implementing targeted overdose prevention strategies in Massachusetts.

The simplified model includes five mutually exclusive health states: Compulsive Opioid Use, On MOUD, Withdrawal, Fatal Overdose, and Death (Figure 1). Individuals in the Compulsive Opioid Use state are actively using opioids without treatment, including both injection and non-injection use. The On MOUD state represents individuals not actively using opioids but currently engaged in medication treatment, such as methadone, buprenorphine, or naltrexone. The Withdrawal state includes individuals who are not using opioids and are no longer receiving treatment, typically those recently discharged from detox or who have discontinued MOUD. The Fatal Overdose state reflects an overdose event that directly results in death and allows no further transitions. The final state, Death, is an absorbing state reached either through overdose or background mortality unrelated to opioid use.

Transitions between states are modeled on a weekly cycle to reflect the short-term dynamics of OUD, including relapse, treatment initiation and dropout, and overdose. Individuals may relapse from either the Withdrawal or On MOUD state back to Compulsive Use, and treatment reentry is permitted from both Compulsive Use and On MOUD. Overdose is only modeled from the Compulsive Use state, reflecting its strong clinical association with untreated active opioid use. Individuals in the On MOUD or Withdrawal states are assumed to be non-active users. Therefore, any return to opioid use, whether it follows treatment discontinuation or the end of an abstinent period, is represented as a transition back to Compulsive Use. As a result, overdose events are not permitted directly from the On MOUD or Withdrawal states.

To account for the elevated risk of overdose following relapse, the model assigns a higher probability of fatal overdose immediately after transitions from Withdrawal to Compulsive Use, particularly during high-risk periods such as post-incarceration or following detoxification. In contrast, while relapse from the On MOUD state also carries a risk of overdose, the probability is lower because these individuals are more likely to retain some tolerance and have continued access to harm reduction resources. Although relapse transitions lead to active use, overdose is modeled probabilistically to occur within the same weekly cycle. This structure aligns with clinical evidence showing that individuals who are opioid-naïve, especially those who have recently completed detoxification or been released from incarceration, face the greatest risk of fatal overdose upon resuming opioid use.

All states except Death allow self-transitions to represent the possibility of remaining in the same state over multiple cycles. This simplified model structure supports flexible modeling of intervention strategies, including the expansion of community-based mobile MOUD clinics, telehealth services, and targeted overdose prevention. At the same time, it retains the core behavioral dynamics of OUD, including relapse, treatment dropout, and post-treatment vulnerability.

Data and Parameter Estimation

Model parameters were derived from multiple sources, including the Massachusetts Department of Public Health (MA DPH), the National Survey on Drug Use and Health (NSDUH), the National Survey of Substance Abuse Treatment Services (N-SSATS), and published literature (Table 1). Mortality and overdose probabilities were calculated using MA DPH statistics, with annual rates converted to weekly probabilities using the transformation $P_{week} = 1 - (1 - P_{year})^{1/52}$.

Treatment engagement and transition rates between health states were estimated using administrative data (e.g., number of individuals receiving MOUD) and published model-based estimates. Probabilities of relapse, overdose, and death were stratified by source states such as withdrawal, MOUD, and compulsive opioid use, incorporating risk multipliers and empirical values from recent simulation studies. MOUD discontinuation rates were weighted by treatment type (methadone, buprenorphine, naltrexone), with treatment composition proportions informed by N-SSATS.

Parameters for transitions between injection and non-injection opioid use, and between active and non-active use states, were drawn from literature and stratified by behavioral patterns. Overdose probabilities following relapse were based on relapse source state and time since relapse (Table 2). Remaining parameters were either calibrated or assumed based on best available evidence.

Statistical Analysis

To evaluate the potential impact of expanding mobile MOUD clinics and implementing targeted overdose prevention strategies, we developed and simulated a simplified discrete-time Markov model over a five-year time horizon using weekly cycles (total of 260 weeks). The model includes five health states: Compulsive Use, On MOUD, Withdrawal, Fatal Overdose, and Death. Transition probabilities were encoded in a 5×5 matrix, specifying weekly movement probabilities between states.

The simulation began with a hypothetical cohort of 300,000 individuals in the Compulsive Use state, reflecting approximate estimates for the population with opioid use disorder (OUD) in Massachusetts. At each weekly time step, the state distribution was updated by matrix multiplication of the current state vector and the transition probability matrix. The model tracks the evolving population in each state over time, along with cumulative overdose deaths and the number of individuals who remain alive (i.e., not in Fatal Overdose or Death).

To incorporate relapse-related overdose mortality, we adjusted transitions from On MOUD and Withdrawal to Compulsive Use by probabilistically splitting a small fraction into direct transitions to Fatal Overdose. These adjustments used published estimates of relapse and overdose risk (Table 3).

Two main scenarios were modeled: (1) Status Quo, which reflects current patterns of treatment engagement and overdose risk, and (2) Enhanced Intervention, which increases the transition

probability from Compulsive Use to On MOUD (simulating mobile clinic outreach) and reduces the risk of overdose during relapse transitions (reflecting the expanded availability of naloxone and peer recovery supports) (Table 4). For each scenario, we calculated weekly trajectories of population distribution, cumulative overdose deaths, and total number of individuals alive. The results were stored as time series and visualized using line plots to compare outcomes over time.

Sensitivity Analysis

To assess the robustness of model outcomes in the presence of parameter uncertainty, we conducted both deterministic and probabilistic sensitivity analyses. For the deterministic component, we varied key transition probabilities individually while holding others constant. Parameters selected for variation included the weekly probability of initiating MOUD from the Compulsive Use state, and the risk of overdose during relapse from both On MOUD and Withdrawal states. For parameters with moderate magnitude, such as those greater than or equal to 0.001, we applied a range of plus or minus fifty percent around their baseline values. For extremely small probabilities, particularly those representing overdose mortality during relapse, we tested several fixed absolute values based on published estimates. These variations allowed us to examine how small changes in assumptions could influence the overall trends in overdose deaths and treatment outcomes.

In addition to the deterministic analysis, we implemented a probabilistic sensitivity analysis using one thousand Monte Carlo simulations for each intervention scenario. In each iteration, transition probabilities were sampled from beta distributions calibrated to reflect empirical means and standard errors derived from administrative records and prior modeling studies. Simulation results were aggregated to produce average values and ninety-five percent uncertainty intervals for key indicators, including cumulative overdose deaths, average distribution across health states, and the relative benefit of enhanced intervention. This comprehensive approach provides a clearer understanding of the range of possible outcomes and helps identify parameters that exert the greatest influence on model projections.

Results

The simplified Markov model was simulated over a five-year time horizon, using weekly cycles for a closed cohort of 300,000 individuals with opioid use disorder (OUD), all initially assigned to the Compulsive Use state (Table 5). Under the Status Quo scenario, the model projected a total of 7,006 cumulative overdose deaths by week 260 (five years), corresponding to approximately 2.34% of the cohort (95% uncertainty interval [UI]: 2.14%–2.52%). Within the first year (week 52), the model estimated 1,796 overdose deaths, or 0.60% of the cohort (95% UI: 0.58%–0.61%). The number of individuals remaining alive at the end of the five-year period was approximately 280,425.

At year five, the projected distribution of individuals across health states included 164,362 (54.79%) in Compulsive Use (95% UI: 47.17%–62.53%), 7,591 (2.53%) in On MOUD (95% UI: 1.93%–3.05%), and 108,471 (36.16%) in Withdrawal (95% UI: 28.82%–43.46%). At the one-year mark, the state distribution showed 253,372 (84.46%) in Compulsive Use (95% UI: 80.03%–87.83%), 11,449 (3.82%) in On MOUD (95% UI: 2.64%–5.13%), and 30,865 (10.29%) in Withdrawal (95% UI: 8.05%–13.39%).

Under the Enhanced Intervention scenario, which included expanded access to MOUD and targeted overdose prevention, the model projected a notable reduction in cumulative overdose mortality. By year five, there were 4,181 overdose deaths (1.39%), representing a reduction of 2,825 deaths (0.94 percentage points) compared to the Status Quo. At one year, cumulative overdose deaths totaled 1,509 (0.50%), a decrease of 287 deaths (0.01 percentage points) relative to the Status Quo. The total number of individuals alive at year five increased to 283,368.

The distribution of individuals across health states at year five under the intervention scenario revealed a significant shift: 71,525 (23.84%) remained in Compulsive Use, representing a reduction of 92,837 individuals (30.95 percentage points) compared to the Status Quo. A total of 12,388 (4.13%) were engaged in MOUD treatment, and 199,455 (66.48%) were in Withdrawal, indicating an increase of 90,984 individuals (30.33 percentage points) in this recovery-related state.

At one year, 179,813 (59.94%) remained in Compulsive Use, while 33,495 (11.16%) were in On MOUD, an increase of 22,046 individuals (7.35 percentage points) compared to the Status Quo. Additionally, 82,682 (27.56%) were in Withdrawal, representing an increase of 51,817 individuals (17.27 percentage points).

In deterministic sensitivity analyses, model projections were most responsive to changes in the weekly probability of MOUD initiation from the Compulsive Use state (CU_to_MOUD) and the overdose risks during relapse from both the On MOUD and Withdrawal states. Lowering the MOUD initiation probability to 0.001338 resulted in an increase in cumulative overdose deaths to 7,875 and a decrease in the alive population to 279,515 at year five. Conversely, increasing this probability to 0.004014 led to a reduction in overdose deaths to 6,283, with a corresponding increase in the number alive to 281,180, and a substantial increase in engagement with MOUD (9,479 individuals) and transitions to Withdrawal (135,424 individuals). These results highlight the significant downstream effect of early treatment access on health outcomes.

Varying the overdose mortality risk from the On MOUD state between 0.000001 and 0.0001 yielded minor differences in total overdose deaths, indicating relative model robustness to this parameter under current assumptions. However, fatal overdose risk following relapse from the Withdrawal state showed greater impact: overdose deaths ranged from 6,992 to 6,998, with small but observable changes in the size of the treatment and abstinent populations.

In probabilistic sensitivity analysis (PSA), we ran 1,000 Monte Carlo simulations sampling transition probabilities from calibrated beta distributions. The enhanced intervention scenario consistently outperformed the status quo in all simulations. At year five, the mean cumulative overdose deaths under the intervention scenario was 4,181, compared to 7,006 (95% UI: 6,405–7,547) under the status quo. The mean number of individuals alive at year five was also higher under the intervention scenario (283,369) than under the status quo (280,435, 95% UI: 279,858–281,050).

Discussion

Key Findings

This simulation study demonstrates the potential of mobile MOUD clinics and targeted overdose prevention interventions to substantially reduce fatal overdose deaths and shift individuals into more stable recovery-related health states within a population of individuals with opioid use disorder (OUD) in Massachusetts. Using a simplified Markov framework inspired by the RESPOND model, we evaluated changes in health state distributions, cumulative overdose mortality, and treatment engagement under both a status quo scenario and an enhanced intervention strategy. The findings suggest that relatively modest improvements in access to MOUD and reductions in relapse-associated overdose risk can generate large public health benefits. These insights support the expansion of low-barrier treatment access and recovery-oriented services within statewide planning and resource allocation.

The enhanced intervention scenario resulted in an estimated 40 percent reduction in cumulative overdose deaths over five years compared to the status quo, which corresponds to more than 2,800 lives saved. In addition, this scenario produced a substantial shift in the distribution of individuals across health states. The population in the Compulsive Use state declined, while more individuals entered or remained in the Withdrawal and On MOUD states. This reflects improved initiation and retention in treatment, as well as greater periods of abstinence from active use. These patterns are consistent with the clinical goal of achieving long-term stabilization for individuals with OUD and underscore the downstream effects of earlier treatment access.

When examining the time-specific trends, the reduction in overdose mortality was relatively modest in the first year, decreasing by only 0.01 percentage points. However, by the end of the five-year period, the cumulative overdose mortality rate decreased by 0.94 percentage points compared to the status quo. This widening gap over time suggests that the intervention becomes increasingly effective as more individuals initiate treatment and remain engaged (Figure 2). As treatment coverage expands, more people achieve sustained recovery and fewer individuals remain trapped in compulsive opioid use. Consequently, the population at highest risk of overdose shrinks over time, leading to progressively larger reductions in overdose deaths. These

findings reinforce the value of long-term investment in MOUD access and demonstrate the compounding benefits of early intervention strategies.

Mechanistic Insights

The model also highlights the importance of targeting periods of elevated overdose risk. In the model, overdose events were assigned only to the Compulsive Use state. However, transitions from Withdrawal and On MOUD contributed indirectly to overdose mortality, as relapse led individuals back to Compulsive Use, where the risk of overdose was then applied. Sensitivity analyses showed that overdose risk following relapse from the Withdrawal state had a measurable effect on model outcomes. This finding supports the prioritization of interventions during critical transition periods, such as after release from incarceration or upon completion of residential detoxification. Strategies such as pre-release MOUD initiation, increased naloxone distribution, and peer support services may help mitigate these risks and contribute to overall reductions in mortality.

Beyond the modeled mechanisms, real-world factors further complicate overdose risk following incarceration. One reason why individuals recently released from incarceration face such extreme overdose risk is the abrupt disconnection from structured environments and the loss of access to regulated care. This sudden transition can create a sense of fragmentation and vulnerability, leading individuals to seek help only from sources that are immediately accessible. Unfortunately, medications for opioid use disorder are often much harder to obtain than illicit opioids. To address this barrier, a community feedback mechanism could be implemented. Community volunteers or hospital-based outreach coordinators could serve as intermediaries, reporting unmet needs in real time and helping direct clinical attention to areas requiring urgent intervention. By using these local insights to guide the establishment of mobile MOUD clinics and telehealth services, healthcare systems could significantly expand treatment accessibility, especially in treatment deserts where patients continue to suffer from inadequate access to care.

Model Structure and Limitations

While the model simplifies certain complexities, it captures the essential behavioral dynamics of OUD. The simplified structure provided a balance between interpretability and fidelity to real-world OUD dynamics. Although it does not account for all dimensions of OUD care, such as heterogeneity in treatment types or transitions between injection and non-injection use, the model retained key behavioral features including relapse, dropout, and treatment reengagement. Using weekly time cycles allowed for fine-grained tracking of short-term transitions, which are critical in the context of OUD. This structure supports practical use in decision-making environments where model transparency and adaptability are essential.

Several limitations of the study should be acknowledged. The model assumes a closed cohort, meaning that no new individuals develop OUD during the five-year horizon. This may underestimate both the ongoing burden of the epidemic and the potential impact of the

interventions. Future versions of the model should consider incorporating incident cases to reflect more realistic population dynamics. In addition, some parameter estimates were based on administrative data and published literature that may not fully capture local variation in care delivery, social determinants of health, or patient characteristics. Although both deterministic and probabilistic sensitivity analyses were conducted to address parameter uncertainty, the model does not include structural features such as comorbid conditions or social networks that could influence treatment outcomes.

Furthermore, the model assumes that health states are mutually exclusive and that individuals are either engaged in treatment or using opioids, but not both. In practice, many individuals may exhibit partial adherence to MOUD while continuing to use opioids intermittently. Incorporating overlapping or mixed states would allow for more nuanced modeling of harm reduction scenarios and real-world behaviors. The current model also does not account for economic costs, which limits its use in cost-effectiveness analyses. Including resource use and treatment costs in future work could support more comprehensive policy evaluations.

Policy Implications

Despite these limitations, the model findings reinforce the value of low-threshold, community-based treatment services in addressing the opioid epidemic. The consistent advantage of the enhanced intervention scenario across all simulations suggests that expanding mobile MOUD clinics and overdose prevention measures could significantly improve public health outcomes. These results provide a strong rationale for policymakers to invest in accessible and flexible treatment delivery models, particularly those that target individuals during vulnerable periods of transition or instability.

Improved Simplified Markov Model

In the initial version of the model, transitions to the Fatal Overdose state were allowed only from the Compulsive Opioid Use state. This structure reflected the model's assumption that individuals in the On MOUD or Withdrawal states are non-active users, and therefore, an overdose must be preceded by a relapse into active opioid use. However, in clinical reality, relapse from these states can be both rapid and fatal, particularly among opioid-naïve individuals who have recently completed detox or discontinued treatment. In such cases, the transition from a treatment or abstinent state to overdose-related death can occur so quickly that it effectively bypasses any sustained period of active use. Although the model allowed for transitions from On MOUD and Withdrawal to Compulsive Use, and then from Compulsive Use to Fatal Overdose within the same weekly cycle, this structure introduced unnecessary rigidity and failed to fully capture the immediacy of relapse-related mortality. In essence, it treated a rapid, lethal relapse as two sequential transitions, when in fact the process may unfold as a single, abrupt event.

Additionally, the representation of the Fatal Overdose state introduced confusion in how overdose deaths were modeled. In the original design, individuals who entered the Fatal

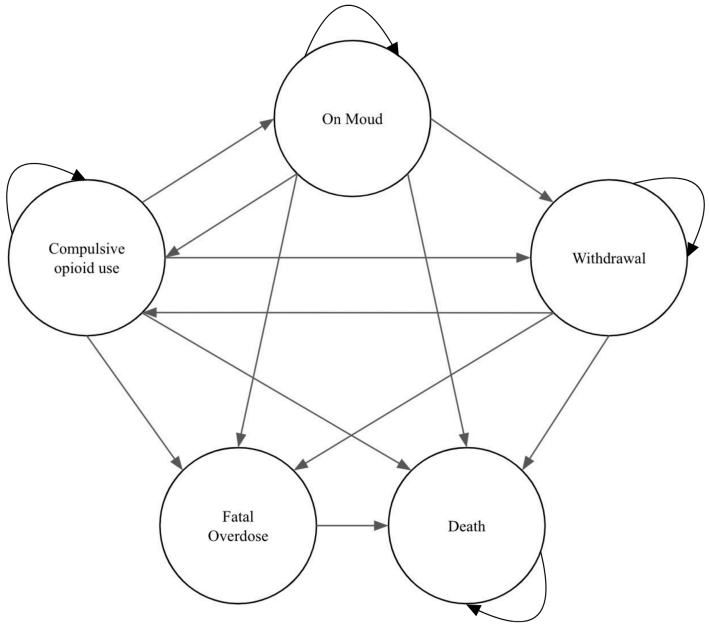
Overdose state were assumed to die immediately, with a transition probability of one from Fatal Overdose to Death in the same time step. While this setup ensured that fatal overdose events led to death, it inadvertently labeled Fatal Overdose as an absorbing state, which in Markov modeling implies permanence or continuation in that state over time. This created a conceptual mismatch, as Fatal Overdose in the model functioned more as a transient condition rather than a long-term or terminal state. The implication that individuals "reside" in the Fatal Overdose state, even momentarily, is inconsistent with the clinical understanding of overdose as an acute, time-sensitive event.

To address both issues, we revised the model structure by removing the Fatal Overdose state and introducing a new Overdose state, which allows probabilistic transitions to either Death or continued survival. In this updated design, relapse from On MOUD or Withdrawal can directly result in an overdose, without requiring a transition through Compulsive Use. This change better captures the immediacy of overdose following treatment discontinuation and reflects real-world patterns in which overdose can occur before a person fully re-engages in sustained opioid use. Furthermore, modeling overdose as a transitional state—rather than a terminal absorbing state—allows the model to represent both fatal and nonfatal overdoses depending on contextual factors such as naloxone availability, emergency medical care, and individual-level tolerance.

This revised structure (Figure 3) enhances both the clarity and realism of the model. It allows for more accurate depiction of high-risk relapse scenarios and avoids structural inconsistencies associated with the earlier use of the Fatal Overdose state. By separating overdose as a probabilistic event with multiple outcomes, the model aligns more closely with clinical experience and improves its utility for evaluating harm reduction strategies and policy interventions.

Appendix

Figure 1: Simplified Markov Model



Notes:

1. **Compulsive opioid use** – Active opioid use (injection or non-injection) with no treatment.
2. **On MOUD** – Non-active opioid use while receiving treatment (e.g., methadone, buprenorphine, or naltrexone).
3. **Withdrawal** – Non-active use following treatment discontinuation or detoxification.
4. **Fatal Overdose** – Death due to opioid overdose.
5. **Death** – Death from other causes or from overdose (absorbing state).

Figure 2: Cumulative Overdose Deaths: Intervention vs. Status Quo

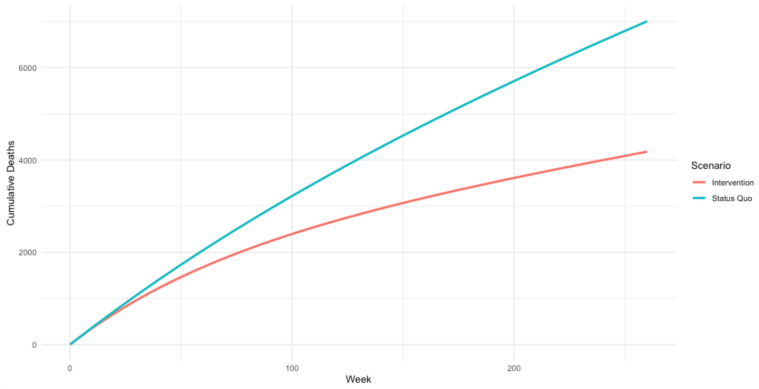


Figure 3: Improved Simplified Markov Model

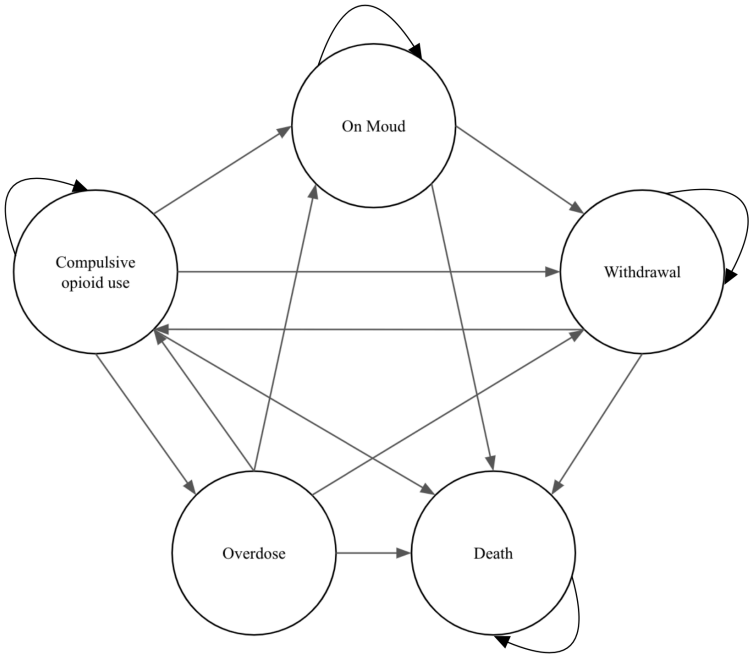


Table 1: Weekly Transition Probabilities

From State	To State	Value	Source
Compulsive Use	On MOUD	0.002675905	MA DPH
Compulsive Use	Withdrawal	0.00058	10
Compulsive Use	Fatal Overdose	0.0001253437	7, MA DPH
Compulsive Use	Death	0.0001683808	MA DPH
Compulsive Use	Compulsive Use	0.9964504	-
On MOUD	Withdrawal	0.0567	7, N-SSATS
On MOUD	Compulsive Use	0.002448776	7, N-SSATS
On MOUD	Death	0.000162375	MA DPH
On MOUD	On MOUD	0.9406888	-
Withdrawal	Compulsive Use	0.00329	11, 12
Withdrawal	Death	0.000162375	MA DPH
Withdrawal	Withdrawal	0.9965476	-
Fatal Overdose	Death	1	-
Death	Death	1	-

Table 2: Probability of Fatal Overdose Within One Week Following Relapse

Relapse From State	Value	Source
On MOUD	0.0000713976	13, 14
Withdrawal	0.0002506874	13, 14

Table 3: Final Weekly Transition Probability (Status Quo)

From State	Compulsive Use	On MOUD	Withdrawal	Fatal Overdose	Death
Compulsive Use	0.996450400	0.002675905	0.000580000	0.0001253437	0.0001683808
On MOUD	0.002448601	0.940688800	0.056700000	0.0000001748	0.0001623750
Withdrawal	0.003289175	0.000000000	0.996547600	0.0000008248	0.0001623750
Fatal Overdose	0.000000000	0.000000000	0.000000000	0.0000000000	1.0000000000
Death	0.000000000	0.000000000	0.000000000	0.0000000000	1.0000000000

Table 4: Final Weekly Transition Probability (Intervention Status)

From State	Compulsive Use	On MOUD	Withdrawal	Fatal Overdose	Death
Compulsive Use	0.989132692	0.010000000	0.0005757406	0.0001244232	0.0001671442
On MOUD	0.002448759	0.940688800	0.0567000000	0.0000000171	0.0001623750
Withdrawal	0.003289342	0.000000000	0.9965476000	0.0000006580	0.0001623750
Fatal Overdose	0.000000000	0.000000000	0.0000000000	0.0000000000	1.0000000000
Death	0.000000000	0.000000000	0.0000000000	0.0000000000	1.0000000000

Table 5: Outcomes of Enhanced Intervention vs Status Quo

Outcome	Status Quo, mean value (95% UI)	Intervention, mean value
Overdose Deaths (Year 1)	1794.946 (1749.351-1834.708)	1508.608
Overdose Deaths (Year 5)	6994.380 (6405.431-7546.728)	4180.659
Alive (Year 1)	295604.5 (295560.8-295654.5)	295918.1
Alive (Year 5)	280435.0 (279857.5-281050.4)	283369.3
Compulsive Use (Year 1)	252519.8 (240089.6-263492.1)	178212.5
Compulsive Use (Year 5)	164694.8 (141521.0-187601.2)	71525.27
On MOUD (Year 1)	11463.40 (7930.144-15402.55)	33306.45
On MOUD (Year 5)	7540.603 (5799.246-9153.694)	12388.40
Withdrawal (Year 1)	31621.30 (24138.62-40162.31)	84399.09
Withdrawal (Year 5)	108199.6 (86457.00-130375.7)	199455.7

Table 6: One-way Deterministic Sensitivity Analysis

Parameter	Value	Overdose Deaths	Compulsive Use	On MOUD	Withdrawal
CU_to_MOUD	0.001338	7874.85	201619.6	4627.94	73267.09
CU_to_MOUD	0.004014	6282.79	136275.7	9479.42	135424.4
OD_OnMOUD	0.000001	7005.97	164361.4	7591.18	108471.2
OD_OnMOUD	0.000100	7006.54	164361.0	7591.16	108471.1
OD_Withdrawal	0.000001	6992.40	164372.0	7591.62	108473.5
OD_Withdrawal	0.000100	6997.94	164367.7	7591.44	108472.6

Supplement:

Figure 2: RESPOND Core Simulation Model

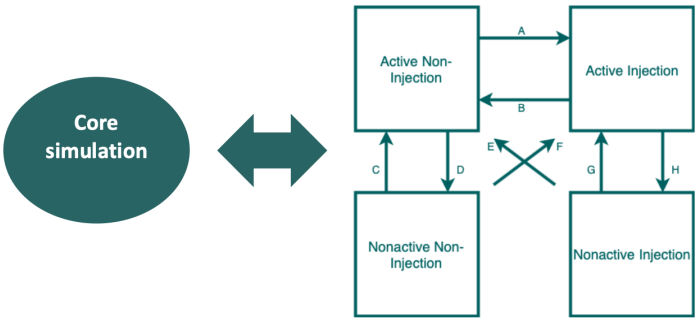
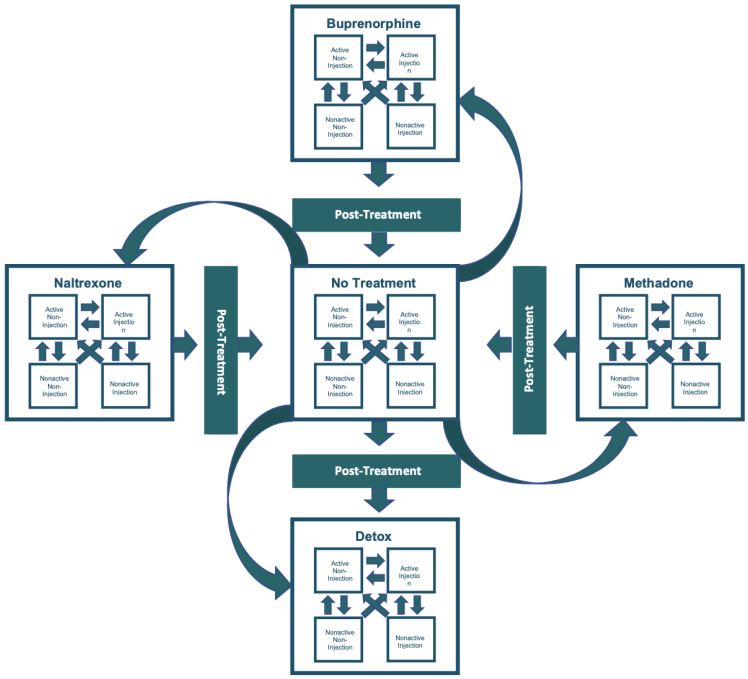


Figure 3: RESPOND's Care Delivery Model



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