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*Article*

# Developing a Tool to Assess the Impact of Simulated Intervention Strategies on Suicide and Suicidal Behaviours in Canada: A Dynamic Modelling & Machine Learning Approach

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**Abstract:** Suicide dynamics form a complex system deeply influenced by interrelated factors, necessitating advanced methodologies for comprehensive analysis. This study pioneers the application of Particle Markov Chain Monte Carlo (PMCMC) methods in suicide research, recognized for their enhanced sampling efficiency over traditional techniques in complex, high-dimensional models. PMCMC is particularly adept at handling non-Gaussian distributions and navigating parameter spaces efficiently, preventing the entrapment in local optima. Utilizing PMCMC, our research simulated a broad spectrum of potential outcomes, clarifying the probable scenarios and their likelihoods, thus enriching the predictive accuracy and understanding of suicide dynamics. These methods facilitated the exploration of dynamic interactions among key risk factors such as mental health issues, trauma, substance use, social isolation, and access to harmful means, whose complex interplays challenge predictive modeling. The study extends previous applications of PMCMC in complex systems like H1N1, opioid crises, and COVID-19 to the domain of suicide, suggesting its potential in enhancing decision-making and intervention strategies. However, limitations due to the model's simplified assumptions and the specificity of the data to certain populations underscore the necessity for broader application to validate findings across varied demographics. In summary, while PMCMC offers robust capabilities for the dynamic modeling of suicide, it requires careful parameter selection and consideration of computational demands. Future research should continue to leverage this approach in more complex settings, enhancing our ability to predict and mitigate suicide risks effectively.

**Keywords:** complex system; data science; machine learning; particle markov chain monte carlo; suicide; system dynamics; systems science, time series data, dynamic modeling, mental health research

## 1. Introduction

Suicide and suicidal behaviour remain among the most pressing public health challenges in Canada [1]. Beyond the immediate loss of life, the knock-on effects of suicide touch families [2], communities [3], and entire societies [4], often leaving wounds that time struggles to heal. Recent statistics paint a somber picture: with suicide consistently ranking among the top causes of death, Canada finds itself grappling with an issue that has not only persisted over time but has also revealed additional layers of complexity with each passing decade [5–7].

Understanding suicide and suicidal behaviour in Canada demands a recognition of its multi-faceted nature [8,9]. A suicide attempt is an outcome influenced by a labyrinth of interwoven factors: from individual-level physical or psychological stressors [10,11], genetic predispositions [12,13], and past traumatic experiences [14,15] to broader societal determinants like economic instability [16], social networks [17,18], cultural nuances [19,20], and systemic healthcare disparities [21,22]. This interplay of personal and environmental factors, punctuated by dynamic feedback loops, makes suicide not just an individual act but a collective phenomenon. Existing literature often falls short in capturing the systemic and dynamic nature of suicide and suicidal behaviours, the way factors cascade, converge, amplify over time, and exhibit reciprocal causality.

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Traditional research methodologies, from epidemiological surveys to sociological studies, have charted the prevalent patterns and determinants of suicide and suicidal behaviours [23–28]. While invaluable, existing methodologies in suicide research often adopt a retrospective lens, primarily analyzing past data to understand current trends and patterns. This approach, however, may not fully capture the rapidly evolving dynamics of suicidal ideation and behaviors, particularly in the context of recent innovations and emerging factors. Notable among these are the profound influences of social media and device usage, as well as the economic and social disruptions that shape modern life. Addressing the multifaceted complexity of suicide, especially in a diverse and constantly changing landscape like Canada, necessitates a forward-looking approach. Such an approach must not only anticipate the outcomes of potential interventions but also be nimble and adaptive to the rapidly emerging realities of our society. It is essential to look beyond the 'rear-view mirror' and develop methodologies that can sense, respond, and adapt to these evolving factors, offering a more dynamic and proactive understanding of suicide risks and prevention strategies.

Simulation modeling represents a powerful tool that allows researchers to conduct virtual experiments on a system. By doing so, it is possible to gauge the potential impact of changes over time in various scenarios. This methodological approach has been widely recognized for its ability to illuminate the consequences of changes in complex systems, particularly in the context of mental health factors, or factors related specifically to suicide-related or self-harm behaviours (early life exposures, substance abuse, domestic violence, homelessness, and unemployment, and their influence on levels of psychological distress [29], mental disorders [30]). This is especially pertinent where experimental research may be impractical or unethical, offering invaluable insights into these sensitive and complex areas[29–35].

One of the core strengths of simulation modelling is its capacity to test "what-if" scenarios [36,37]. For example, while studies have shown the potential benefits of reducing access to lethal means of suicide [38–40], a simulation can quantify the potential ripple-through effects of such an intervention across different demographics and timeframes. Similarly, strategies like firearms restrictions [41] and poison control [42] have been advocated for, given their direct correlation with means-restriction and suicide prevention. Yet, to fully grasp their long-term implications, especially when considering them in conjunction with other interventions such as primary prevention and post-attempt care, it's essential to conduct an intricate, systemic analysis. The unique ability of simulation modeling to examine the combined effects of multiple interventions within the complex, non-linear dynamics of these systems underscores its necessity in this field. Another pivotal scenario involves the aftermath of non-lethal suicide attempts. Literature suggests that individuals who have made a prior suicide attempt are at an elevated risk for subsequent attempts and potential suicide [43**? ?** ]. This makes interventions aimed at lowering the rate of relapse for suicidal re-ideation post-attempt a crucial area for exploration. Using simulation, we can seek to anticipate the long-term impact of enhanced post-attempt care systems and gauge their effectiveness in breaking the cycle of re-ideation and attempt.

In the specific context of suicide and self-harm research, simulation modeling emerges as an exceptionally dynamic and responsive tool for policymakers. Grounded in a rich array of data encompassing mental health trends, social media influences, and behavioural patterns, it provides a nuanced and actionable roadmap. This roadmap is not only instrumental in evaluating potential outcomes specific to suicide prevention and post-intervention care but also in prioritizing and sequencing interventions to optimize their impact. By focusing on diverse types of outcomes, including immediate risks and long-term behavioural changes, simulation modeling aids in crafting more effective strategies for suicide and self-harm prevention. By simulating these scenarios, decision-makers are equipped with actionable insights, rooted in evidence, to navigate the challenges of suicide prevention in Canada.

Prior research has explored various modeling techniques to understand and predict suicide trends, but few have integrated the sophistication offered by these advanced methods.

Filtering techniques, in particular, play a pivotal role in the dynamic modeling of suicide. Kalman Filtering (KF) [44] is well-noted for its effectiveness in linear systems with Gaussian noise, providing a

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robust framework for estimating the state of dynamic systems under uncertainty [44]. However, its application in suicide dynamics is limited due to the non-linear nature of such systems and its inability to estimate static parameters crucial for long-term predictions.

Particle Filtering (PF) extends the capabilities of KF by accommodating non-Gaussian noise and non-linear relationships, making it more suitable for the complex interplay of factors involved in suicide dynamics [45]. However, PF alone often struggles with the joint estimation of both dynamic and static parameters [46].

PMCMC stands out by combining the strengths of Monte Carlo simulation with the PF framework, enabling the estimation of latent and dynamic parameters even in highly non-linear systems [47]. This capability is crucial for developing more accurate and comprehensive models of suicide, where both the temporal dynamics and static characteristics of risk factors need to be simultaneously considered.

Deciphering the multifactorial causes of suicide necessitates an exploration into a deeply complex, intertwined system, wherein various elements are not only intricately interconnected but also interact in ways that defy simple summation. This dynamic system, integral to understanding suicide and suicidal behaviours, is characterized by reciprocal causality, where factors like mental health, social environments, and personal experiences influence each other bidirectionally. The influence of multiple overlapping networks – familial, social, and professional – further adds to the complexity. These networks exhibit path-dependence and lock-in phenomena, where past events and choices significantly shape current suicidal risks and behaviours, creating a challenging cycle to break. Additionally, the nonlinear interactions within various environmental contexts – such as cultural, economic, and media influences – play a substantial role in shaping individual behaviours and vulnerabilities. This intricate web of factors, each with its unique trajectory and impact, demands an approach that can adeptly navigate and unpack the layers of this coupled non-linear dynamic. Such an understanding is crucial to developing targeted interventions and preventive strategies that address the broad spectrum of influences leading to suicide and self-harm. One of the promising methodologies in this realm is the System Dynamics (SD) approach. Stemming from feedback control theory, SD goes beyond just quantifying variables, but also deals with visualizing, understanding, and predicting how these variables change in relation to each other over time [48]. For instance, the relationship between economic hardships, mental health deterioration, and suicide rates is not static. A sudden economic downturn might accelerate mental health issues, which in turn might influence suicide rates, with elevated suicide incidence imposing further mental health burden. Capturing such dynamic interplays and reciprocal effects demands a framework robust enough to model the feedback loops inherent to such systems. In the realm of suicide research, SD can offer insights into the cascading effects of determinants, both immediate and lagged [49–51]. For example, while a societal shift might impact the immediate stressors leading to suicidal ideation, its long-term effects on systemic healthcare disparities or specific cultural attitudes towards mental health might only become apparent over extended periods. SD can track and predict these intricate trajectories, providing a macroscopic view of potential future trends based on current actions or interventions. However, the promise of SD is not without challenges. The stochastic occurrence and intricate nature of suicide, with its myriad determinants and feedback loops, introduces uncertainties, especially when parameters are estimated from sparse or incomplete data sets. This is where the PMCMC method steps in [52].

PMCMC is a powerful statistical tool designed to handle the complexities and uncertainties associated with dynamic models subject to both stochastic evolution and uncertainty with regards to parameters [47]. In scenarios where traditional modelling techniques struggle,PMCMC methods shine by addressing the inherent limitations of data availability and the randomness in process evolution. PMCMC distinguishes itself by simultaneously estimating the static parameters and the hidden states of a model as it evolves stochastically over time. This dual focus on static and dynamic elements allows it to navigate the uncertainties present in complex models effectively. By concentrating on sequences of random variables, PMCMC provides a pathway to outcomes that are both robust and reliable, overcoming the constraints that often hinder traditional approaches [47].

Combining SD with PMCMC brings together the strengths of both methodologies [52]. While SD lays down the framework for understanding the structure and feedback loops of the suicide system, PMCMC refines this understanding by addressing happenstance in process evolution, inaccuracies in measured data, uncertainties regarding parameter values and with regards to the current system state, and missing data. This combined approach promises to provide a comprehensive, granular perspective on the dynamics of suicide in Canada. Far from being merely theoretical, this approach endows policymakers, healthcare professionals, and community leaders with actionable insights. It offers a dynamic lens through which the complex interplay of determinants can be examined, facilitating the creation of interventions that are responsive to the evolving nature of the issue. Importantly, it underscores the capability to obtain an ongoing, continually updated comprehension of the current scenario through data reintegration. This iterative process of grounding and re-grounding findings in empirical evidence, coupled with theoretical frameworks, enables a nuanced interpretation of data. Consequently, it ensures that decision-making is informed by a blend of current realities and foundational theories, aligning strategies closely with the dynamic and multifaceted nature of challenges such as suicide and self-harm.

Having set the stage with the complexities and multifaceted nature of suicide and suicidal behaviours in Canada, This work sought to investigate several aspects: (1) To explore the shifting landscape of suicidal behaviours in Canada, it is essential to assess the trends and changes observed in recent years. This analysis forms a crucial part of the background situation, providing a comprehensive summary rather than framing it as an investigatory question. Given the availability of data, this section will delineate how patterns of suicidal behaviour have evolved, identifying key factors contributing to these trends. This approach ensures a solid foundation for understanding the current state of suicidal behaviours in Canada, setting the stage for deeper investigation into the causes, impacts, and potential interventions. (2) To investigate the efficacy of the PMCMC method in enhancing SD models, this study focuses on its impact on the accuracy and other relevant metrics in modeling the complex nature of suicide and suicidal behaviours in Canada. By integrating PMCMC, the research aims to refine the SD model's precision, ensuring it captures the multifaceted and dynamic aspects of suicidal behaviours with greater validity. This approach allows for a rigorous assessment of how PMCMC contributes to improving model reliability, providing deeper insights into the intricate factors influencing suicide trends and enabling the development of more targeted interventions. (3) What impact can changing parameter values, as modeled in our "what-if" scenarios, have on the broader dynamics of suicide and suicidal behaviour in the Canadian context? In essence, this research journey aims to bridge advanced computational techniques with an understanding of the determinants of suicide, striving for a synthesis that could light the path toward effective prevention and intervention strategies in Canada.

## 2. Methods

This research adopts a quantitative approach, "cross-levering" SD modelling and PMCMC techniques to elucidate the intricacies of suicide dynamics in Canada. The study spans between 1981-2018, capturing historical and current patterns to assess future progression of suicidal behaviours.

### *2.1. Suicide and Suicidal Behaviour SD Model*

In this project, we have developed an SD model focused on understanding suicide and suicidal behaviours. The model outlines the progression from suicidal ideation, which involves contemplating suicide, to actual suicidal behaviours. This progression is depicted as a series of stages or states an individual may go through, serving as a key element in our dynamic model's stochastic characterization. The stochastic state-space model serves as the foundation for implementing the PMCMC algorithm. This advanced method is specifically utilized for the joint estimation of model parameters and state variables through sampling, enabling the prediction and comprehension of future states by leveraging both observed data and the intrinsic dynamics of the model.

Our decision to consider incoming data on a monthly basis aligns with the availability of key time-series datasets on suicide counts in Canada, enhancing the model's relevance and comparability with real-world observations.

Previous work has highlighted the fundamental role that gender plays in suicidal behaviours. Multiple studies have consistently shown variations in both the prevalence and methods of suicide attempts between men and women. For instance, men might opt for more violent methods, leading to higher lethality rates, while women might exhibit higher rates of ideation or non-fatal attempts [53]. To account for these disparities and to enrich the model's descriptive and predictive capabilities, the SD model is sex-stratified and method-stratified. Such stratification enables us to capture the inherent heterogeneity and nuances in suicidal behaviours and tendencies between genders.

To offer a visual understanding of how these elements interplay and to provide an overarching view of the conceptual framework of this research, we have mapped out the general structure of the sex- and method-stratified SD model. This map, detailing each state and the possible transitions between them, can be found in Figure 1. Through this figure, readers can gain an overview of the model's scope and the stages of the processes characterized by the model.

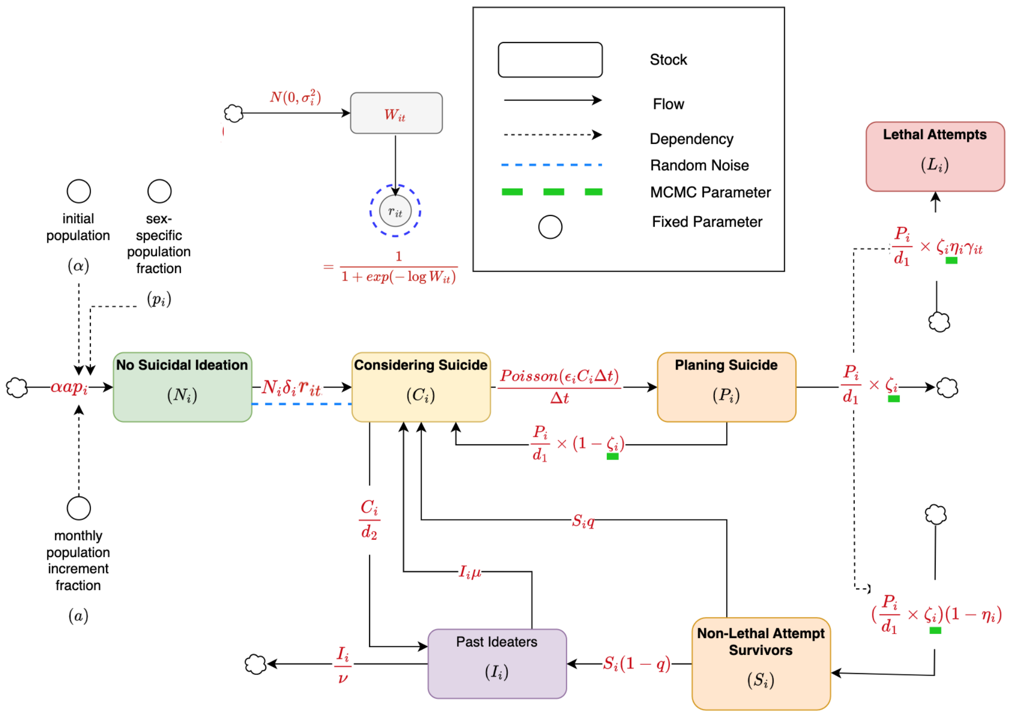


**Figure 1.** The structure of the stratified suicide progression SD model is depicted. It should be noted that while stratification by sex, and method is integral to the model, it is not explicitly shown in the diagram. Each component or 'stock' in the model is subject to such underlying stratification, affecting respective processes and interactions within the system. [The model was modified from the Australian suicide prevention model [30] for use in Canada].

The SD model employed in this study draws its foundational structure from the Australian suicide model, as documented by Page et al. (2017) [30]. However, to suit the specifics of the Canadian demographic and, more pertinently, the requirements needed for particle filtering – both on its own and within the PMCMC algorithm – extensive modifications were instituted.

This detailed adaptation of the Australian model, involving the transition from 'conveyor stocks' to conventional stocks and flows to facilitate integration with PF and PMCMC techniques, is documented in the supplemental information [See Appendix A]. This adjustment ensures our Canadian SD model maintains its conceptual integrity while aligning with the mathematical rigour required for advanced computational methods.

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The series of ordinary differential equations used in the SD model is given below; names correspond to those in a labelled stock-and-flow diagram for the model in Figure 1:

$$
\begin{aligned}
\frac{dN_i}{dt} &= \alpha a p_i - N_i \delta r_{it} \\
\frac{dC_i}{dt} &= \frac{P_i}{d_1} \times (1 - \zeta_i) + S_i q + I_i \mu - \frac{Poisson(\epsilon_i C_i \Delta t)}{\Delta t} - \frac{C_i}{d_2} \\
\frac{dP_i}{dt} &= \frac{Poisson(\epsilon_i C_i \Delta t)}{\Delta t} - \left(\frac{P_i}{d_1} \times \zeta\right) - \left(\frac{P_i}{d_1} \times (1 - \zeta)\right) \\
\frac{dS_i}{dt} &= \left(\frac{P_i}{d_1} \times \zeta\right)(1 - \eta_i) - S_i q - S_i(1 - q) \\
\frac{dI_i}{dt} &= S_i(1 - q) + \frac{C_i}{d_2} - I_i\left(\mu + \frac{1}{\nu}\right) \\
\frac{dL_i}{dt} &= \frac{P_i}{d_1} \times \zeta \eta \gamma \\
\frac{dW_{it}}{dt} &= N(0, \sigma_i^2)
\end{aligned}
$$

where the subscript $i \in 1,2$ represents male and female, respectively.
$r_{it} = \frac{1}{1+exp(-\log W_{it})}$ is the inverse-logit of any number $W_{it}$ at time $t$, measured for $i \in 1,2$, i.e., males and females separately, where $dW_{it}$ is a standard Weiner process characterized as $dW_{it} \sim N(0, \sigma_i^2)$ [54]..The Weiner process adds a random walk in the incidence where people are first time ideating about suicide.

The initial values of the stocks and the fixed values of the parameters of the suicide SD model are given in Table 1 and 2, respectively .

**Table 1.** Initial Values of the Stocks in the System Dynamics Model.

| Stock | Description | Value | Source |
|---|---|---|---|
| $N_1$ | Initial number of males without suicidal ideation | 9069052 person | Estimated from Statistics Canada [55] |
| $N_2$ | Initial number of females | 14026049 person | Estimated from Statistics Canada [55] |
| $C_1$ | Initial number of males ideating about suicide | 250000 person | Assumption based on Page et al. (2017) [30] |
| $C_2$ | Initial number of females ideating about suicide | 250000 person | Assumption based on Page et al. (2017) [30] |
| $P_1$ | Initial number of males planning about suicide | 5000 person | Assumption based on Page et al. (2017) [30] |
| $P_2$ | Initial number of females planning about suicide | 5000 person | Assumption based on Page et al. (2017) [30] |
| $S_1$ | Initial number of males making non-lethal attempts | 0 person | Page et al. (2017) [30] |
| $S_2$ | Initial number of females making non-lethal attempts | 0 person | Page et al. (2017) [30] |
| $I_1$ | Initial number of past ideaters (male) | 0 person | Page et al. (2017) [30] |
| $I_2$ | Initial number of past ideaters (female) | 0 person | Page et al. (2017) [30] |
| $L_1$ | Initial number of males, who made lethal attempts | 186 person | Assumption |
| $L_2$ | Initial number of females, who made lethal attempts | 100 person | Assumption |

### *2.2. Particle Markov Chain Monte Carlo (PMCMC): A Brief Overview*

This section provides a basic PMCMC algorithm [47]. Note that there are different variants of PMCMC, such as the Particle Gibbs sampler, and some details might vary depending on the specific variant or application context. Given a state-space model:

1. State transition: $x_t \sim f_t(x_t|x_{t-1}, \theta)$
2. Observation model: $y_t \sim g_t(y_t|x_t, \theta)$

**Table 2.** Parameters in the SD Model.

| Parameter | Description | Value | Source |
|---|---|---|---|
| $\alpha$ | Initial Canadian population | 33628895 person | Statistics Canada [55] |
| $p_1$ | Fraction of male | 49.5% people | Statistics Canada [55] |
| $p_2$ | Fraction of female | 50.5% people | Statistics Canada [55] |
| $a$ | Monthly net growth rate of the population | 0.095% | Estimated from Statistics Canada [55] |
| $\gamma_{1t}$ | Effect of monthly time-series suicide data (males) | [0.886,0.951,0.896, 1.032, 1.036,1.093,] 1.05,1.048,1.042 0.993,0.992,0.980] | Estimated from Statistics Canada [56] |
| $\gamma_{2t}$ | Effect of monthly time-series suicide data (females) | [0.859,0.955,0.912, 1.057,1.021,1.104 1.032,1.025, 1.062, 0.988,1.008,0.976] | Estimated from Statistics Canada [56] |
| $\delta_1$ | Hazard rate of the males having suicidal ideation for the first time | 0.013 | Assumption |
| $\delta_2$ | Hazard rate of the females having suicidal ideation for the first time | 0.009 | Assumption |
| $\epsilon_1$ | Hazard rate of making concrete suicide-related plans (males) | 40% per year | Page et al. (2017)[30] |
| $\epsilon_2$ | Hazard rate of making concrete suicide-related plans (females) | 40% per year | Page et al. (2017) [30] |
| $\zeta_1$ | Hazard rate of the males attempting suicide | 1% per month | Assumption |
| $\zeta_2$ | Hazard rate of the females attempting suicide | 1% per month | Assumption |
| $\eta_1$ | Fraction of males making lethal attempts among all male attempts | 0.043 | Assumption based on WHO (2022) [57] |
| $\eta_2$ | Fraction of females making lethal attempts among all female attempts | 0.015 | Assumption based on WHO (2022) [57] |
| $\mu$ | Hazard rate of development of suicidal ideation among past ideaters | 5% per year | Assumption |
| $\nu$ | Average life expectancy of the post-ideating population | 30 years | Page et al. (2017) [30] |
| $d_1$ | Mean duration of suicidal planning | 1 month | Page et al. (2017) [30] |
| $d_2$ | Mean duration to cease suicidal ideation | 4 months | Assumption |
| $q$ | Fraction of population quickly relapsing into suicidal ideation (following a non-lethal attempt) | 2% per month | Page et al. (2017) [30] |
| $dt$ | Integration time step | 0.05 month | Assumption |

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where

- $x_t$ is the state at time $t$
- $y_t$ is the observation at time $t$
- $\theta$ are the model parameters

1. **Initialize:** Choose an initial value $\theta^{(0)}$ and set m = 0.
2. **Repeat until convergence:**

   (a) Set $m = m + 1$.
   (b) **Particle Filter with $\theta^{(m-1)}$:**

      i. Initialize $w_0^{(i)} = 1$
      ii. For each time point $t = 1, ..., T$:

         A. For each particle $i = 1, ..., N$:

            - Sample $x_t^{(i,m-1)} \sim f_t(\cdot|x_{t-1}^{(i,m-1)}, \theta^{(m-1)})$.
            - Compute unnormalized weight $W_t^{(i)} = w_{t-1}^{(i)} * g_t(y_t|x_t^{(i,m-1)}, \theta^{(m-1)})$.

         B. Normalize weights: $w_t^{(i)} = \frac{W_t^{(i)}}{\sum_{j=1}^{N} W_t^{(j)}}$.
         C. Resample $N$ particles $x_t^{(i,m-1)}$ based on weights $w_t^{(i)}$.

   (c) Compute approximate marginal likelihood:

$$L(\theta^{(m-1)}) = \prod_{t=1}^{T} \left( \frac{1}{N} \sum_{i=1}^{N} w_t^{(i)} \right)$$

   (d) Propose a new parameter value $\theta^*$ from a proposal distribution $q(\theta^*|\theta^{(m-1)})$.
   (e) **Particle Filter with $\theta^*$:** (Repeat the steps in 2(b) using $\theta^*$ instead of $\theta^{(m-1)}$)
   (f) Compute the acceptance ratio:

$$\alpha = \min\left(1, \frac{L(\theta^*)q(\theta^{(m-1)}|\theta^*)}{L(\theta^{(m-1)})q(\theta^*|\theta^{(m-1)})}\right)$$

   (g) Accept or Reject:

      i. Sample $u \sim \text{Uniform}(0, 1)$.
      ii. If $u < \alpha$, set $\theta^{(m)} = \theta^*$. Otherwise, $\theta^{(m)} = \theta^{(m-1)}$.

### *2.3. Model Recalibration and Likelihood Estimation*

In dynamic, real-world scenarios, the underlying systems themselves are constantly evolving, necessitating a shift from static modeling approaches to adaptive models that can accurately reflect these changes [58–60]. This evolution is not only a characteristic of the systems we study but also a fundamental aspect of the modeling process itself [48]. As modelers incorporate new information, their models undergo a process of evolution, becoming more refined and better suited to address the complexities of the real world [52]. This iterative process of adaptation and evolution underscores the need for models that are capable of evolving in response to new data and insights [52]. This is precisely the purpose of re-grounding the model with every newly acquired data point, which serves to update the estimate of the latent state, including evolving parameter values. Such re-grounding serves as a form of dynamic re-calibration that ensures that the model stays relevant, accurate, and aligned with the unfolding real-world trends [52].

The concept of generating particles that mirror hypotheses about the actual system state is central to particle filtering. Here, the likelihood function plays a pivotal role. It evaluates how each particle (or hypothesis about the state) aligns with the actual observed data. In simpler terms, it answers the question, "Given this particle's state, what's the likelihood that we'd observe the given empirical data?" This function's value is used to update the particle's weight, determining its influence in subsequent steps.

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With empirical observations consisting of ten time series datasets (for males and females separately, and then further stratified by sex and methods), this methodology showcases its flexibility. For every new data point, the likelihood function offers a comparative metric, juxtaposing the model's projections with real-world observations. The value of the composite likelihood is deduced by multiplying the individual likelihoods [52]. This composite value ensures that every data point is considered in conjunction, capturing the fact that a single system must simultaneously explain the observations considered in each successive likelihood function. At timepoints where an observation is not available from one of the datasets, the value of the associated likelihood is treated as 1.0.

Our approach to articulating the likelihood function for this model draws on the authors' collection of past successes with negative binomial-based likelihood functions in particle filtering applications for diverse problems [45,61–66]. Furthermore, the utility of MCMC-based approaches in similar contexts reinforces our choice [67,68]. Building upon the proven strategies and insights garnered from these works, our model is designed with simplicity and effectiveness at its core. This design ethos, reflecting the principles of streamlining complex systems while maintaining robust analytical capabilities, is in line with the approach observed in previous studies [52,68].

Mathematically, the overarching likelihood function for our particle filtering model, denoted as $L$, is defined as the product of sub-likelihood functions [52,67,68]. Each of these functions targets a specific subset of empirical datasets, grounding the model:

$$\begin{aligned} L &= L_{Male} \times L_{Female} \\ &\times L_{Male,Firearms} \times L_{Female,Firearms} \\ &\times L_{Male,Poisoning} \times L_{Female,Poisoning} \\ &\times L_{Male,Hanging} \times L_{Female,Hanging} \\ &\times L_{Male,Others} \times L_{Female,Others} \end{aligned}$$

Each sub-likelihood function expresses the likelihood of observing specific empirical data based on corresponding variables within the dynamic model [68], and adheres to a negative binomial distribution.

### *2.4. Data Collection and Stratification*

The largest volume of empirical evidence in this study consisted of time series data on suicide counts, a critical health metric of paramount significance in public health research. This data was distinguished by sex, providing a gendered perspective on suicide trends in Canada—a significant lens given the known disparities and differences in suicide rates, methods and lethality between men and women [69]. It is important to note that while total sex-stratified counts were reported on a monthly basis, counts stratified by both sex and method were reported annually

Our choice of sourcing from the Death Database of Canadian Vital Statistics [56] reflects the fact that this repository by Statistics Canada [70] is renowned for its accuracy, credibility, and comprehensive collection methods. The use of this source helps ensure that the model is grounded on reliable, nationally representative data. The provision of this data by the Public Health Agency of Canada [71] further underscores the importance and critical role of the data in public health policymaking.

### *2.5. Simulated Scenarios*

#### 2.5.1. Baseline Scenario

We make use of a baseline scenario to characterize the historical situation. In this scenario the PMCMC algorithm operates in tandem with the suicide SD model, interpreting empirical data in a manner consistent with the range of possibilities arising from the stochastic simulation model across the entire timeline. The foundational data comes from traditional public health surveillance empirical datasets, with the model continually refining its predictions based on past and current suicide-

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related death trends. This simulation utilizes 1000 particles over 20000 iterations. At each iteration, dichotomous acceptance is recorded, simultaneously sampling values of both static parameters and the time-evolution of state variables.

2.5.2. Hypothetical Counterfactual Scenarios

To fully harness the potential of the SD model and evaluate the impact of various interventions on suicide, several "what-if" scenarios have been conceptualized (*however, it is important to note that these scenarios have not yet been executed; they are designed for future research to explore the potential effects of different interventions. Detailed implementation strategies, such as adjusting specific parameters, are planned but have not been applied in the current study.*):

1. **Primary Prevention of Suicidal Ideation:** This scenario examines the effect of proactive measures aimed at reducing the onset of suicidal ideation in the population, such as through building resilience. The specific interventions of concern could encompass mental health awareness campaigns, community support programs, and early intervention mechanisms [72]. By simulating this scenario, we seek to quantify the potential reduction in suicide and suicidal behaviours stemming from such preventive initiatives.
2. **Reduced Access to Suicide Means:** This scenario simulates the effect of limiting access to common means of suicide (e.g., reduced access to harmful substances [73,74] and hanging [75], and firearms restrictions [28,75,76]) is significantly restricted or regulated. The anticipated outcome is a potential reduction in suicide attempts and, consequently, deaths. Given that firearms, poisoning or toxic substances, and hanging are among the leading methods of suicide in many regions, understanding their impact is crucial.
3. **Enhanced Post-attempt Care:** Recognizing that individuals who have been past ideaters are at a heightened risk of attempt or re-attempt, this scenario models an environment with reinforced post-attempt care systems [77]. This could involve specialized medical care, counselling, community support, and regular follow-ups.
4. **Lowering Relapse Rates:** Here, we simulate the effect of interventions designed to reduce the rate of suicidal re-ideation immediately following a non-lethal attempt. By integrating potential measures such as continuous therapy, support groups, and mental health awareness, we aim to understand the long-term benefits of reducing relapse [78].

For each of these scenarios, the SD model, paired with the PMCMC algorithm, offers insights into the potential effectiveness of the scenario, so as to inform policymakers in shaping future interventions. These simulations not only capture the immediate ramifications of the interventions but also their ripple-through effects on the broader sets of suicide processes in Canada.

*2.6. Software Implementation*

Throughout this research, a codebase hosted on GitHub, named CEPHIL, was utilized extensively. This repository facilitates the integration of high-performance, computationally intensive PF and PMCMC algorithms, implemented in C, with R modules designed for data manipulation, statistical analysis, and visualization. This integration has provided a robust framework that significantly supported the achievement of the research objectives.

It is important to note that the codebase is subject to ongoing development, contributing to future academic outputs. Given the extensive collaborative nature of this project and the foundational, model-agnostic logic encapsulated in the codebase, the complete code is not included in this document. Detailed examination of the codebase is available to interested members upon request.

## 3. Results

Employing PMCMC with our modified suicide model enables sample-based estimation of parameters and states throughout time, using the gathered empirical data. The Particle Filter process itself incorporates dynamic variables. Results from simulation trials shed light on both the observed states and the latent states of the system. In Figure 2-6, the 2D histogram illustrates the sample stock values as a distribution through MCMC iterations. The x-axis represents time in the model, with each unit corresponding to a month, and the entire time horizon spanning 108 months or 12 years.

Figure 2-3 presents a 2D histogram of state samples, computed across MCMC iterations, that provides estimates of the trend of suicide in Canada during 2010-2018. The x-axis covers 108 months, and the y-axis portrays model state values. The density indicated in the figure directly reflects the approximation to the posterior distribution, based on weight-based sampling of particles. As can be recognized from the figure, these state values align well with empirical data, which is superimposed on the density. The average calculated from sampled particles are also presented in the figures as blue lines. In essence, the distribution of sampled values mirrors the model's perceived current state; throughout each particle filtering, the empirical data at each point refines this distribution through a Bayes' update.

The strong alignment of the empirical data with the highest posterior density region, suggests a strong inferential accuracy in the model. While formal evaluation is not conducted here, a comparison of the prediction results with estimation of the posterior results using empirical data suggests that the model offers significant predictive accuracy over the span of months; However, the inherent stochastic nature of the model, which captures the evolving character of suicide dynamics, limits the feasibility of making tightly bounded predictions over the long term. It is important to recognize that many relevant phenomena in the world are reasonably characterized as stochastic, where month-by-month point predictions are inherently challenging. Examples of such phenomena include large-scale isolating events like pandemics [79,80], shifts in economic strength or industry automation leading to higher unemployment, technological advancements (e.g., the rise of smartphones and social media and their correlation with increased loneliness, depression, and suicide attempts), media influences on suicidal ideation (such as the observed increase in suicides following the release of "13 Reasons why on Netflix") [81], and the availability of means (e.g., the accessibility of synthetic opioids). These elements underscore the complexity of accurately forecasting suicide dynamics and highlight the need for models that can adapt to and reflect these stochastic influences.

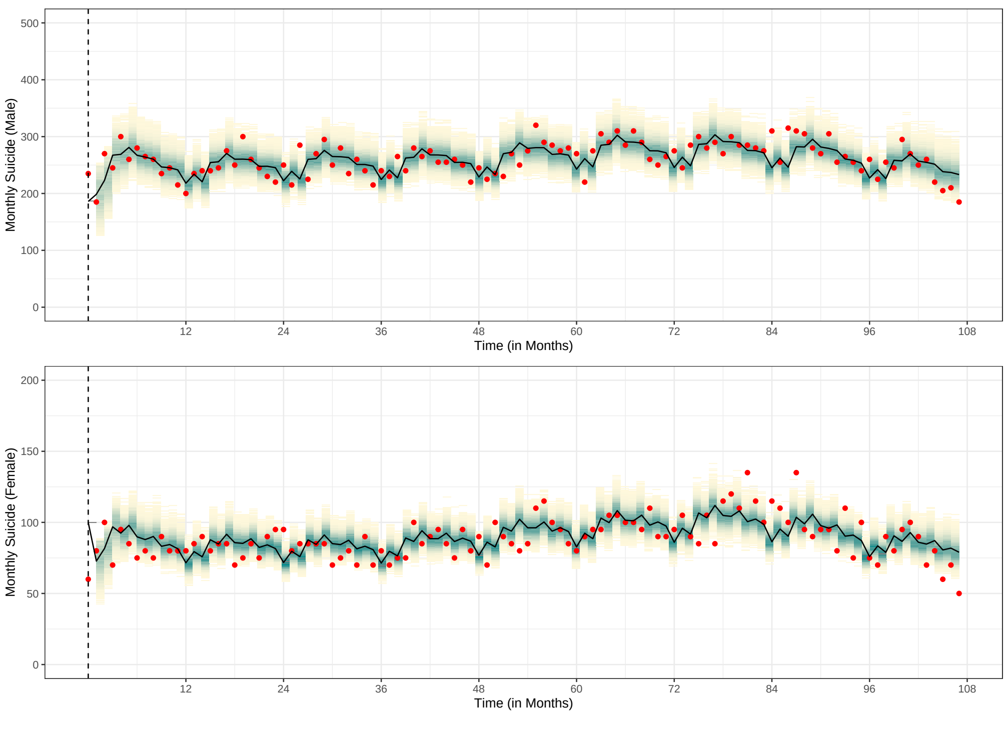


**Figure 2.** Monthly empirical data compared to corresponding model posterior distribution of suicide. [*Red points are the empirical data; histogram bins are particle values where darker colour indicates higher density. Blue line indicates the average of the particle values*].

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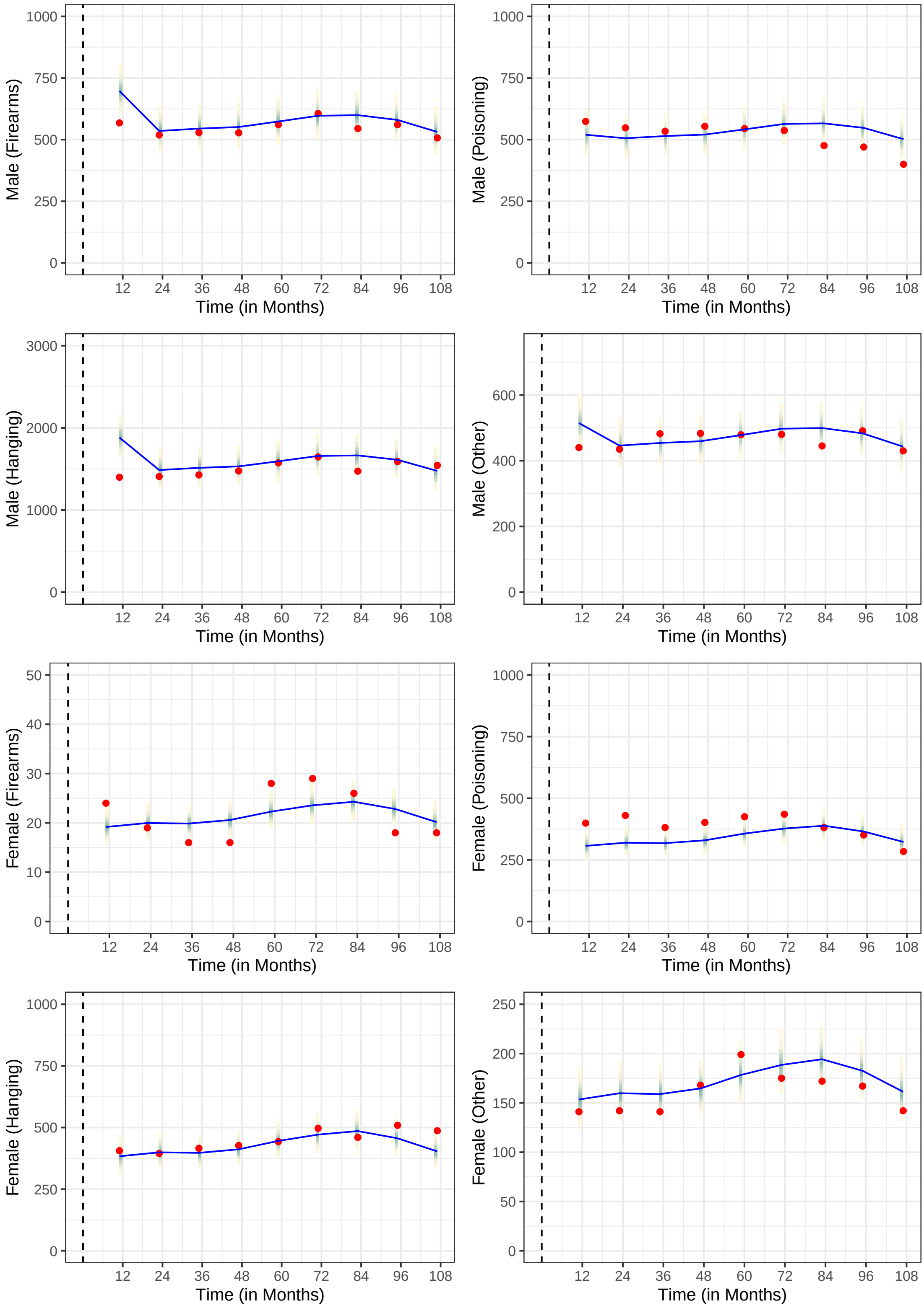


**Figure 3.** Yearly method-specific empirical data compared to corresponding model posterior distribution of suicide.[*Red points are the empirical data; histogram bins are particle values where darker colour indicates higher density. Blue line indicates the average of the particle values*].

Figure 4-6 depicts latent states of the model – states for which no empirical data is available. The y-axis reflects the dynamic stock values; because of the lack of corresponding empirical data, no comparative values are shown. For stocks like 'Considering', 'Planning', and 'Non-Lethal Attempts' the

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y-axis displays the count of individuals. The density of the stock is indicative of particle distributions, which approximate statistical probabilities.

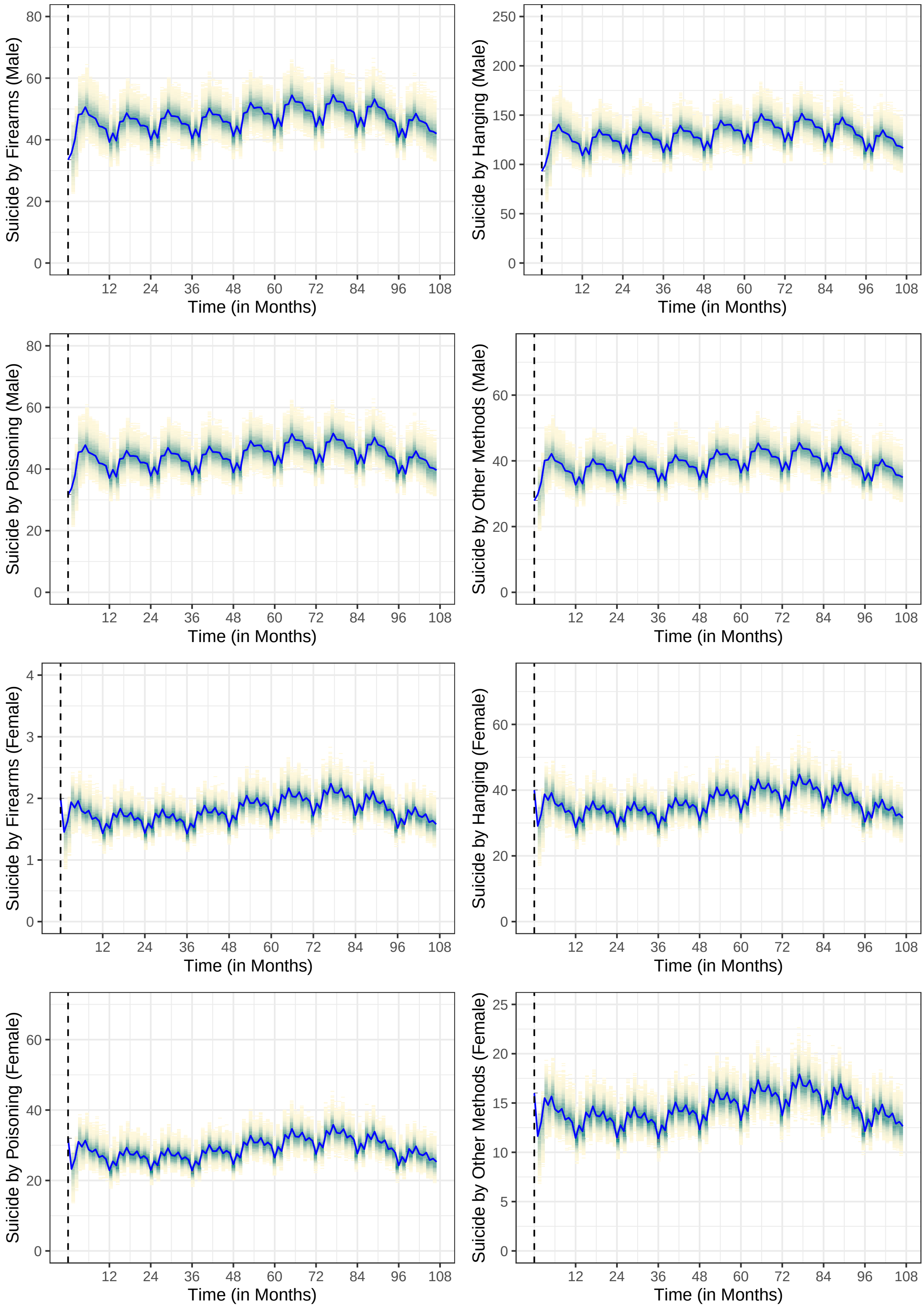


**Figure 4.** Monthly method-specific model posterior distribution of suicide, overlaid by the sample mean of suicide over all particles. [*Histogram bins are particle values where darker colour indicates higher density. Blue line indicates the average of the particle values*].

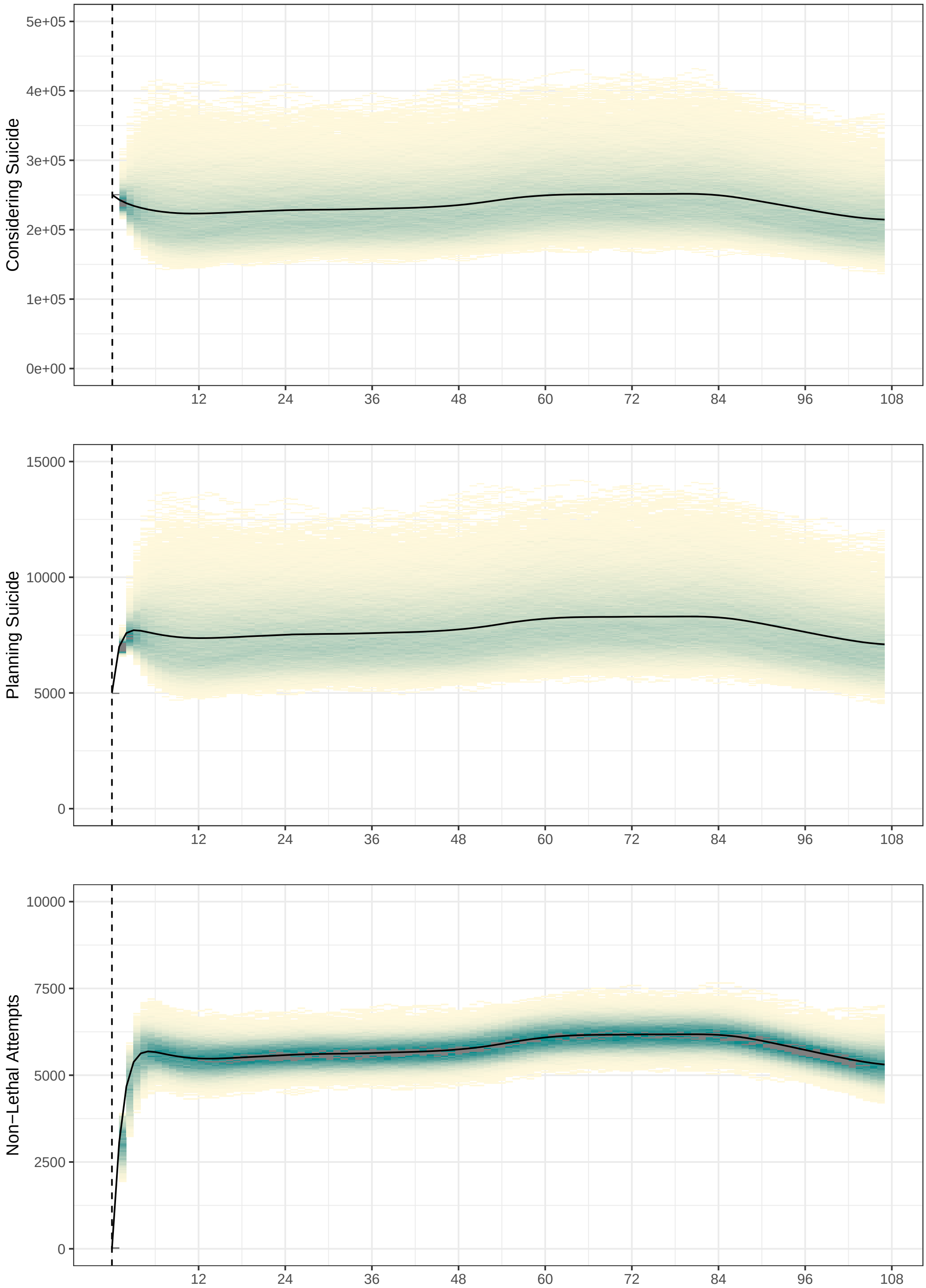


**Figure 5.** Monthly latent states of the model posterior distribution of the males considering suicide, planning about suicide, and making non-lethal attempts per month, overlaid by the sample mean of the corresponding states over all particles.[*Histogram bins are particle values where darker colour indicates higher density. Black line indicates the average of the particle values*].

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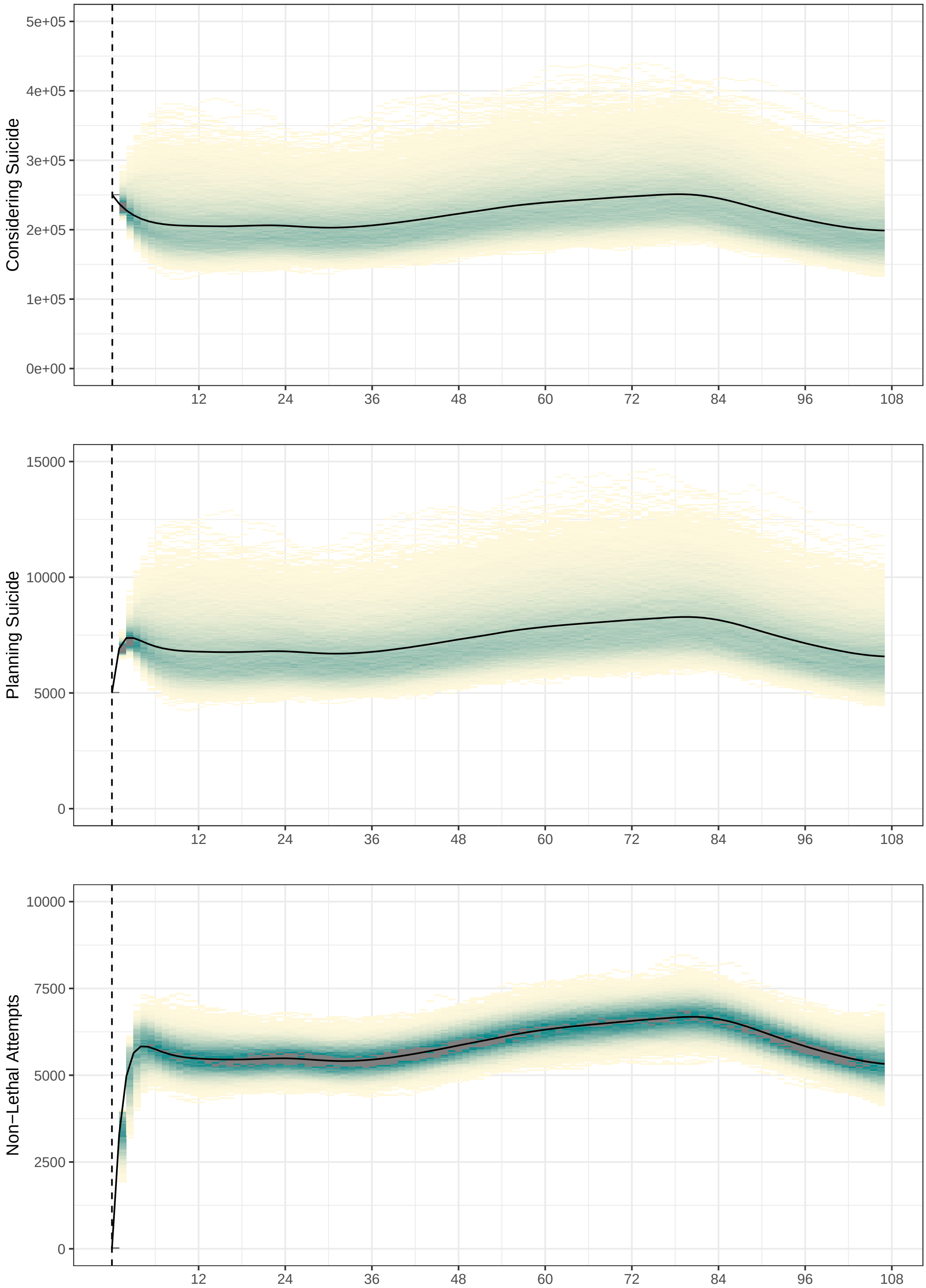


**Figure 6.** Monthly latent states of the model posterior distribution of the females considering suicide, planning about suicide, and making non-lethal attempts per month, overlaid by the sample mean of the corresponding states over all particles.[*Histogram bins are particle values where darker colour indicates higher density. Black line indicates the average of the particle values*].

Figure 7 also showcases dynamic variables in a 2D histogram. For instance, the fraction of initial ideation about suicide for females remains stable, while fraction of initial ideation about suicide for

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males fluctuates. Secondly, the most pronounced difference that stands out is the fact that males have higher levels of the initial fraction of ideation compared to men. The evolution of both these dynamic parameters undergo a random walk with the same value for their standard deviation parameter (0.2

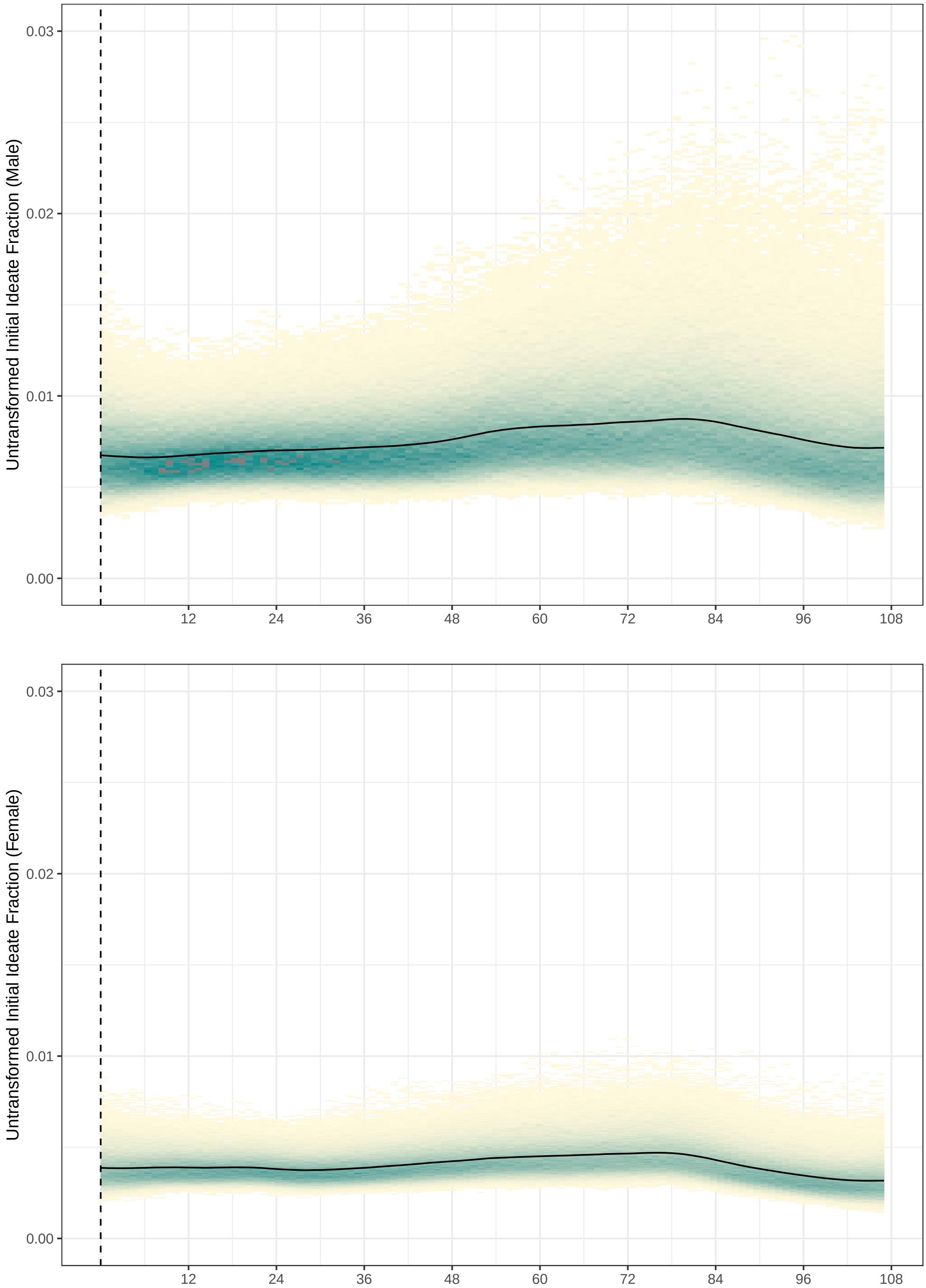


**Figure 7.** Sampled dynamic variables of the suicide model [i.e., the fraction of people initially ideating about suicide per month].[*Histogram bins are particle values where darker colour indicates higher density. Black line indicates the average of the particle values*].

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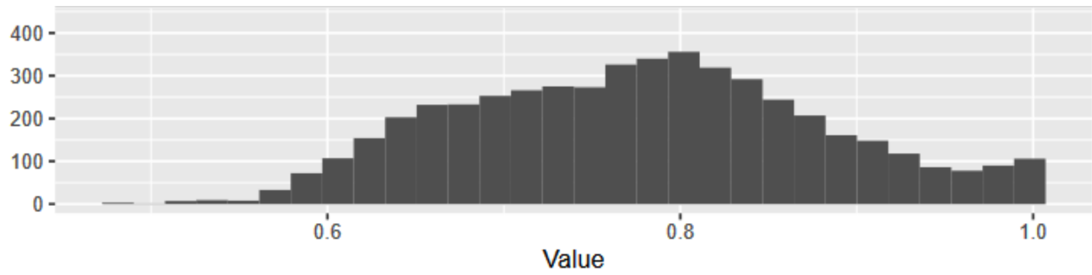
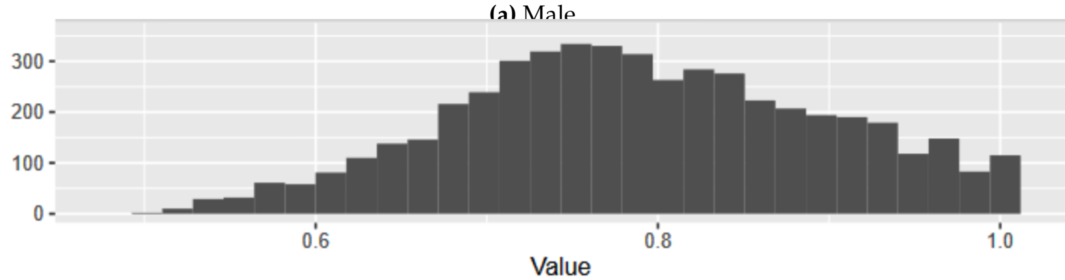
Figure A1 in Appendix A displays the estimated MCMC parameter values obtained from the model of suicidal behaviours in Canada.

Histograms of the parameters sampled by the MCMC algorithm for male and female participants are presented in Figure 8. The parameters represent the proportion of the total attempts that were captured as lethal or non-lethal events, helping to understand sex-specific trends in the attempts of suicide. Both histograms show that the most frequent estimations of the fraction of attempts cluster around 0.8 for both genders, with male participants showing slightly more variability towards higher fractions. These findings suggest a strong central tendency in behaviour, with minor variations between genders in the extremes of the distributions.




**(a)** Male




**(b)** Female

**Figure 8.** The histogram of the parameters sampled by the MCMC algorithm (i.e., fraction of total attempts).

## 4. Discussion

The interplay of factors shaping and being shaped by suicide constitutes a complex system [82–84] whose investigation strongly benefits from a systems science approach. PMCMC methods can provide more efficient sampling than traditional methods, particularly in high-dimensional and complex models [85,86]. PMCMC methods use a set of particles to explore the parameter space, which can help to avoid getting stuck in local optima and improve the overall exploration of the parameter space [87]. PMCMC methods can handle non-Gaussian distributions associated with measurement error and associated with the perturbations in system evolution, which is useful when working with complex systems and many types of non-normally distributed epidemiological data [88,89]. PMCMC methods can be particularly valuable when working with time series data, as they can help to capture the dynamics of the system over time and can predictive accuracy.

Employing PMCMC methods enabled us to conduct a comprehensive series of simulations, effectively navigating the inherent uncertainties within the system under study. This approach facilitated a detailed exploration of the diverse potential outcomes, allowing for a nuanced understanding of their distribution and likelihood. Specifically, the simulations were instrumental in pinpointing the scenarios most likely to occur, alongside providing quantifiable estimates for the probabilities associated with the baseline scenario. This process was crucial in mapping out the varied possibilities and their implications, thus offering a richer, data-informed picture of potential future states..

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PMCMC methods offer valuable when working with dynamic systems that involve multiple variables and uncertain relationships between those variables [52]. In the case of suicide, for example, many factors may contribute to the risk of suicide, including mental health issues [90–92], particularly trauma [93,94], substance use [90,95,96], social isolation [97,98], social media communication [99,100] and access to firearms [101,102], among others. These factors may interact in complex ways, making it difficult to predict the outcome of changes to any one factor of suicide.

Our findings are consistent with previous research that has demonstrated the value of PMCMC methods in other complex systems, such as the H1N1 pandemic [103], the opioid crisis [52], and COVID-19 [68]. However, to our knowledge, this is the first study to apply PMCMC methods to the study of suicide dynamics. Our results suggest that such methods may be valuable for researchers and policymakers working to understand and prevent suicide.

There are notable limitations to this study. For example, while this work drew on model structures that demonstrated robustness in previously published work, the resulting model was based on a simplified set of variables and relationships, and more complex models may yield different results. Additionally, this study was focused on a specific population and geographic area, and it is still being determined whether the findings from this study would generalize to other populations and settings. PMCMC methods can be computationally expensive, particularly when working with large datasets or complex models, making them impractical for some applications. PMCMC methods themselves involve several hyper-parameters that need to be chosen appropriately for the specific problem, including the number of particles, the proposal distribution selection, and the tuning of the parameters. Selecting appropriate parameters can be challenging, and poor choices can result in poor sampling efficiency or biased results. PMCMC methods can suffer from particle degeneracy [104], which occurs when some particles have much higher weights than others, leading to poor parameter space exploration and reduced efficiency.

However, there are circumstances where the comprehensive capabilities of PMCMC are not strictly required. For instance, in Agent-Based Models (ABMs) that focus on the discrete actions of individuals rather than estimating continuous parameters, or in models where stochastic elements are minimal or absent, simplifying the need for PMCMC's intensive computations. Additionally, scenarios that only necessitate point estimates or that do not engage deeply with parameter uncertainty may benefit from more straightforward modeling approaches. Such contexts highlight the need for a nuanced understanding of the problem at hand, guiding the selection of an appropriate method that balances complexity with computational efficiency and model fidelity.

Overall, while PMCMC methods, offer several advantages, they also require careful consideration of their limitations and proper selection of parameters to ensure accurate and efficient modelling results.

In conclusion, this study provides evidence that PMCMC methods can be a valuable tool for understanding the dynamics of suicide and identifying effective interventions to reduce its incidence. Future research should explore the use of these methods in more complex models and diverse populations with other scenarios included.

## 5. Conclusion

I have demonstrated a promising framework that can support rapid learning from diverse lines of emerging evidence related to suicide. By using a dynamic model that incorporates a wide variety of evidence and theory, this approach provides a rigorous means of estimating the state of the underlying system on an ongoing basis, even in areas where little direct data is available. It also allows for probabilistic anticipation of future trends, leveraging the latest evidence. This capacity for the model to adapt and learn from emerging evidence, which is automatically incorporated into the model, is vital given the large uncertainties associated with the processes underlying suicide, its pervasive and cross-sectoral elements, and the fast-shifting nature of its dynamics. While dynamic models like the one introduced here and machine learning techniques applied to lines of evidence [29–35,105,106] can

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provide great insight, we believe that the ability to quickly learn from emerging evidence and update models and understanding accordingly, as enabled by this approach, will provide much greater gain than any single approach.

**Author Contributions:** Conceptualization, R.Z., and N.D.O.; methodology, R.Z., and N.D.O.; software, R.Z., J.M., and N.D.O.; validation, R.Z., and J.M.; formal analysis, R.Z.; investigation, R.Z., and J.M.; writing—original draft preparation, R.Z.; writing—review and editing, R.Z., and N.D.O.; visualization, R.Z., N.D.O., and J.M.; supervision, N.D.O. All authors have read and agreed to the published version of the manuscript.

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**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** This research utilized secondary data sourced from Vital Statistics and the Discharge Abstract Database, which had already been stripped of any personal identifiers, along with published estimates from Statistics Canada. Consequently, no ethics approval was necessary for this study.

**Data Availability Statement:** Data used in this study are available from the authors upon request.

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**Conflicts of Interest:** The authors declare no conflict of interest.

## Abbreviations

The following abbreviations are used in this manuscript:

PMCMC: Particle Markov Chain Monte Carlo;
COVID: Coronavirus Disease;
KF: Kalman Filtering;
PF: Particle Filtering;
SD: System Dynamics;
MCMC: Markov Chain Monte Carlo;

## Appendix A SD Model Adaptation from Australian SD Model of Suicide

At the heart of the Australian model was a departure from traditional SD methods, utilizing what was termed as a “conveyor stock." In essence, such stock was a platform-centric technique designed to finely track the temporal progression of individuals residing within specific stocks. Individuals would remain in these stocks for a predefined time span before transitioning to other stocks, a process often accompanied by some degree of attrition, colloquially termed "leakage." Although conceptually robust, these non-standard elements posed challenges in integration with PF and PMCMC, which demanded a more conventional and mathematically rigorous structure. To address this, we restructured the Canadian SD model, substituting these conveyor stocks with conventional stocks and flows. This alteration retained the original intent of characterizing dynamics but facilitated a smoother integration with PMCMC techniques.

The recalibration of flow values in our model, necessitated by its integration with PF and PMCMC to enhance predictive accuracy.

Lastly, the Australian counterpart delved deeper into the nature of suicide attempts, distinguishing between lethal and non-lethal endeavours and further subdividing them based on intent—whether these were deliberate or accidental. However, this granularity posed practical challenges for our Canadian context. Notably, Canadian data repositories do not record information concerning the intention behind non-lethal attempts. Furthermore, ascertaining the intent behind lethal attempts is practically challenging, given the inherent difficulties in discerning the motivations of deceased individuals. Given these constraints and for the sake of coherence and data availability, we chose to forego these additional layers of stratification of intent in our model.

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## Appendix B Sampled MCMC Parameters

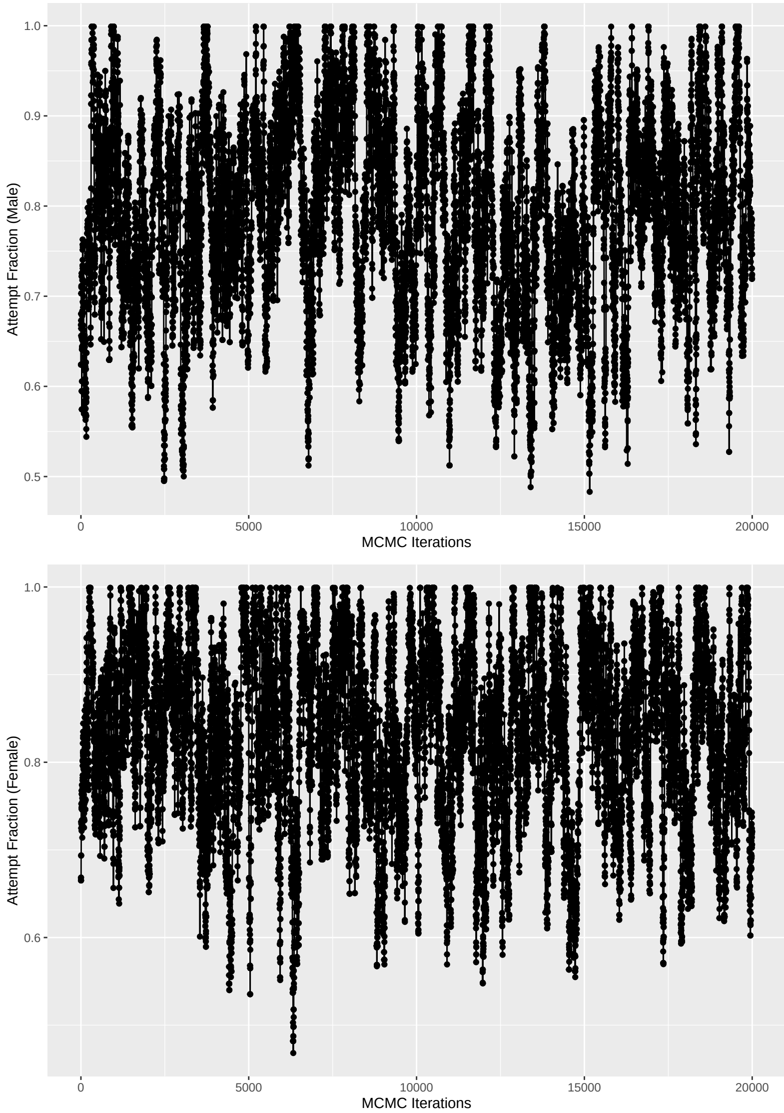


**Figure A1.** The trace plot of parameters sampled by MCMC algorithm: from fraction of total attempts.

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