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Veteran Suicide Prevention in the USA: Evaluating Strategies and Outcomes Within Face the Fight

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Abstract

Veteran suicide remains a critical public health crisis in the United States, with rates nearly twice those of the general population. Addressing this challenge requires multiple evidence-based interventions across settings. This paper presents a system dynamics model developed within the Face the Fight™ veteran suicide prevention initiative to evaluate and optimize strategies from 2022 to 2032. The model integrates peer-reviewed evidence on intervention effectiveness, subject-matter expert calibration, and annual updates from Veterans Affairs and grantee data to estimate the potential population-level impact of suicide prevention. The model organizes veterans by levels of suicide distress and estimates the impact of interventions in an initial three target areas aligned with a public health approach to suicide prevention: creating protective environments (e.g., secure firearm storage), strengthening access and delivery of suicide care (e.g., suicide-specific clinical programs), and identifying and supporting people at risk (e.g., suicide screening). Model results indicate that focusing solely on high-distress veterans is insufficient to reduce suicide rates to those of the general population, while balanced portfolios combining clinical, community, and firearm-safety approaches yield the greatest projected benefit. Sensitivity analyses demonstrate the model's responsiveness to population distress distributions and intervention capacities, underscoring the need for a balanced, scalable strategy. Evaluating suicide-prevention impact is inherently challenging, but the model provides a dynamic and transparent framework for assessing investment effectiveness, refining strategies, and forecasting long-term outcomes. Its adaptability ensures ongoing insights to guide funding priorities, informs data-driven policy, and extends to other populations and public health challenges where multiple interventions interact to influence outcomes.

Keywords: veteran suicide; suicide prevention; system dynamics; modeling suicide risk; public health; suicide risk reduction

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1. Introduction

Veteran suicide remains a leading public health crisis in the United States and a top priority for the Department of Defense and the U.S. Department of Veterans Affairs (VA) [1–3]. The 2024 National Veteran Suicide Prevention Annual Report exposed troubling data showing the veteran suicide rate is nearly 60% higher than non-veteran adults, with more than 6000 deaths each year [1,2]. Since 2001, over 125,000 veterans have died by suicide [1,2]. This staggering number illustrates the magnitude and persistence of this tragedy. Despite decades of investment and coordination across federal and

community systems, population-level declines have proven difficult to achieve and to measure impact [3]. This reality highlights the urgent need for comprehensive, coordinated, and multifaceted suicide prevention strategies that address the unique experiences and challenges faced by veterans.

Measuring suicide-prevention impact remains a central challenge for both the U.S. and international public-health communities. Suicide data are delayed by one to two years, vary in quality across jurisdictions, and may often undercount deaths due to misclassification or stigma [4–7]. Non-fatal behaviors are inconsistently captured, leaving major gaps in understanding how prevention programs influence population-level outcomes. These constraints make it difficult to link program activity to observed change. The result is an evidence base that is fragmented and heavily reliant on retrospective analyses, which is an enduring obstacle for veteran-focused initiatives.

Recent critiques of traditional suicide-prevention paradigms emphasize that suicide remains inherently unpredictable at the individual level, underscoring the need for approaches that focus on understanding system-level mechanisms rather than forecasting individual events [8]. Dynamic, population-based models provide a structured way to integrate evidence across interventions and contexts, allowing for simulation of potential outcomes and more informed strategic planning for suicide prevention. Dynamic system modeling offers a rigorous framework for integrating heterogeneous data and testing potential outcomes of prevention portfolios. Widely used in fields such as infectious-disease control, diabetes, and opioid-overdose prevention [8], these models combine empirical data with subject-matter-expert consensus to estimate population-level effects. Recent global and U.S. evaluations have identified modeling and simulation as critical next steps for system-level evaluation [9].

Veterans face intersecting risk factors that elevate suicide vulnerability, including high rates of post-traumatic stress disorder, depression, anxiety, and substance use compared with civilians [1,2,10–17]. Yet most veterans who die by suicide have not recently engaged in VA care, underscoring persistent barriers such as stigma, limited awareness of resources, and logistical or cultural obstacles to help-seeking [1,2,13]. Lethal means safety adds another critical dimension, as firearms are involved in more than 70% of veteran suicides [1], highlighting the importance of integrating lethal-means education with mental-health care within community and clinical settings. These realities reinforce the need for comprehensive, public-health strategies that coordinate prevention across systems of care.

Preventing veteran suicide requires a comprehensive public health approach that includes both community-based prevention and clinical intervention. The Department of Veterans Affairs (VA), the Department of Defense (DoD), the White House, the Substance Abuse and Mental Health Services Administration (SAMHSA), and the Centers for Disease Control (CDC) have initiatives and strategic plans mobilizing attention, resources, and subject-matter experts [1–3,14,15]. Effective suicide prevention strategies must be holistic, integrative, and evidence-based, drawing support from various sectors, including healthcare providers, veteran organizations, policymakers, and community groups. Community prevention efforts involve outreach programs, peer support networks, and public health campaigns designed to reduce stigma and encourage help-seeking behavior among veterans. Clinical interventions include evidence-based treatments such as cognitive-behavioral therapy [16,17], suicide management (e.g., Crisis Response Planning, Safety Planning Intervention) [18,19], and psychiatric care, tailored specifically to the needs of the veteran population [20]. Ultimately, an effective approach must integrate community outreach with clinical care, ensuring that veterans, whether engaged in the community or seeking clinical

support, receive the comprehensive care they deserve. Suicide prevention initiatives should focus on combining these strategies to have the largest impact possible.

Face the Fight™ is an innovative, eight-year initiative founded in 2022 by USAA, Humana Foundation, and Reach Resilience, an Endeavors Foundation. The initiative's primary goal is to reduce the veteran suicide rate to match or be lower than that of the general population. Face the Fight employs a comprehensive, science-backed strategy that integrates multiple interconnected components: a public awareness campaign, grantmaking to non-profit organizations, and coalition building. The public awareness campaign focuses on bringing awareness, reducing stigma, and promoting help-seeking behaviors among veterans. The coalition, which includes a diverse range of organizations and stakeholders, serves as a platform for disseminating best practices, sharing knowledge, and coordinating efforts to maximize impact across sectors. Through its grantmaking efforts, Face the Fight identifies and scales effective programs—both clinical and community-based—ensuring that proven suicide prevention interventions reach the veterans who need them most.

Face the Fight is guided by the CDC public health approach to suicide prevention and prioritizes funding programs that align with this framework [14]. The initial grants awarded through the Face the Fight Charitable Fund concentrated on three critical areas of the CDC model: creating protective environments, strengthening access to and delivery of suicide care, and identifying and supporting individuals at risk. The initiative also emphasizes funding programs with the potential to be scaled, enabling them to reach more veterans across the United States. By supporting both programmatic and infrastructural development, Face the Fight enhances the capacity of grantees to maximize their impact. This comprehensive strategy addresses immediate risks while fostering long-term protective factors for veterans.

In this context, a dynamic data model refers to a system-level simulation that estimates suicide-related outcomes for the veteran population under different intervention scenarios. *Lives saved* denotes the modeled difference between projected deaths by suicide in the absence of interventions and those expected when Face the Fight, or any suicide-prevention initiative, activates interventions. These are population-level projections rather than individual counts, updated annually with new VA and grantee data.

Assessing the impact of suicide prevention initiatives like Face the Fight presents significant challenges. A system dynamics model provides a robust framework for evaluating this impact by incorporating key inputs, such as the reach of interventions funded through Face the Fight [21]. The model simulates changes in the distress levels among veterans and evaluates how different interventions may reduce suicide risk over time. It is designed not only to measure the impact of the initiative but also to guide funding decisions by estimating the potential lives saved through different interventions.

A dynamic public-health model integrating existing evidence, subject-matter expertise, and estimated reach of grantees was developed to estimate the potential population-level impact of Face the Fight, a philanthropic portfolio on veteran suicide. The model's structure, inputs, and assumptions illustrate how system-level simulation can guide strategic investment and complement traditional evaluation approaches. By aligning with global calls for data-driven, system-level suicide-prevention strategies [5], the work demonstrates how dynamic modeling can translate evidence into coordinated and sustainable action.

2. Methods

2.1. Data Inputs and Annual Model Updates

Data from funded organizations are compiled through structured end-of-grant reports summarizing program reach, population characteristics, and outcomes. These reports provide both quantitative indicators and qualitative implementation summaries used to

contextualize program performance. The evaluation team standardizes data across grantees and reviews them for internal consistency and completeness.

Each year, the model is updated using aggregated data from three primary sources: (1) the VA's National Veteran Suicide Prevention Annual Report, (2) Face the Fight grantee reports, and (3) peer-reviewed literature on intervention effectiveness. These updates refine parameters such as veteran population size, suicide mortality, and intervention reach and performance. Parameter adjustments are reviewed by the Face the Fight Scientific Advisory Committee to ensure that updates reflect current evidence and real-world implementation conditions. This annual review process maintains model transparency, enables iterative improvement, and ensures alignment with emerging evidence and field conditions.

2.2. Model Structure

The backbone of the model divides the population into three categories of psychological suicide-related distress: Low, Moderate, and High (Figure 1). While we initially considered using suicide risk instead, risk of suicide is volatile can increase as quickly as within minutes, and at the policy level, suicide-related distress is a preferred, less volatile indicator that changes over a longer time horizon. The distress level is based on an interplay between a person's risk factors and protective factors and is widely recommended for population indicators of suicide vulnerability [6,9]. The more risk factors someone has and the fewer protective factors, the higher their suicide-related distress. While some people in every distress category attempt suicide, the higher their distress, the more likely it is that they will attempt suicide. Risk factors can be modifiable including treatable medical or mental health concerns or employment challenges, or permanent like previous suicide attempts, history of homelessness, traumatic brain injury (TBI) and chronic pain. Examples of protective factors include social connections, stable housing, strong coping strategies, etc.

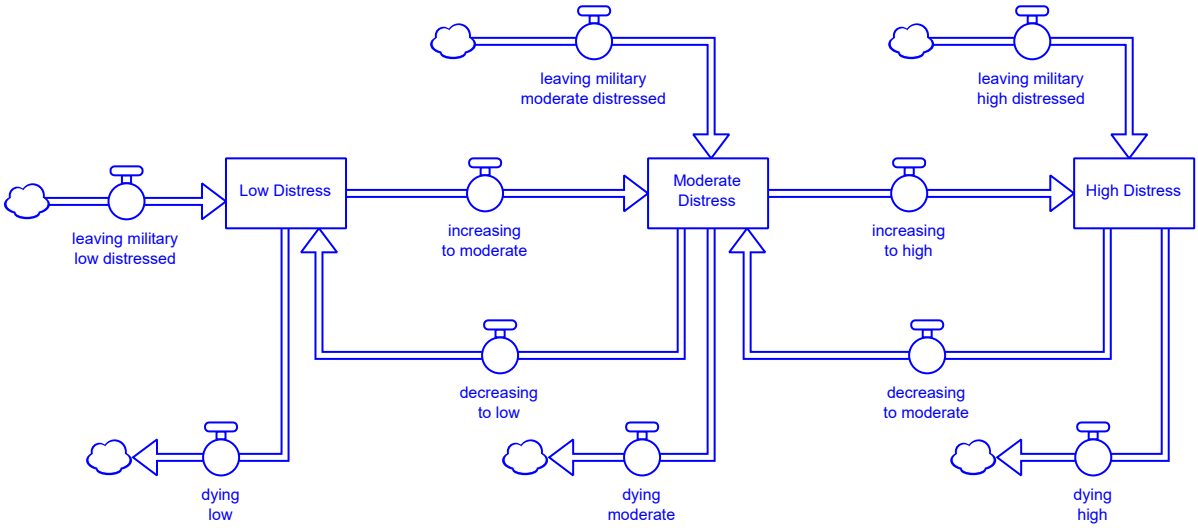


Figure 1. Population stocks in the suicide prevention model.

Low distress is defined as those with modifiable risk factors and strong protective factors. Someone with multiple risk factors and few protective factors is considered to be in moderate distress. Finally, high-distress individuals have few, if any, protective factors and have experienced an acute precipitating event (i.e., financial crisis, recent loss of employment or housing).

Veterans enter the respective stocks based on their distress level when they leave the military. They only leave the overall population if they die, either through natural causes

or by suicide. Over time, they will transition between the different distress levels. After working with many subject matter experts (SMEs), it was decided that, without treatment, the proportion of the population in each category most likely stays constant across the simulation time frame. Therefore, the model is calibrated to maintain those proportions as closely as possible through the base case simulation run (no interventions). After reviewing current literature and the functioning model, the SMEs decided 73% of the population is in low distress, 23% are in moderate distress, and the remaining 4% are in high distress. These same proportions are applied to those leaving the military.

There are specific factors that can be turned on to simulate harsher conditions that would result in more people in higher distress levels, for example, a recession or higher than normal disability or addiction. These have not been used so far. The full set of model equations appear in Appendix A.

2.3. Intevention Pathways

The model supports several interventions, in both clinical and community settings. Each intervention has a determined effectiveness in reducing suicide attempts. In addition, each intervention can be either permanent (for at least the length of the simulation) or can fade away over time. Tables 1–3 list the initial supported interventions that are part of the Face the Fight portfolio with their effectiveness and their permanence.

Table 1. Clinical interventions with their effectiveness and permanence.

Intervention	Effectiveness	Permanence
Screening [22]	0.15	1 month
Brief Cognitive Behavior Therapy (BCBT) [16,17]	0.55	permanent
Crisis Response Planning (CRP) [18,19]	0.50	permanent
Caring Contacts [23]	0.50	permanent

Table 2. Strategic storage interventions with their effectiveness and permanence.

Intervention	Effectiveness	Permanence
Lock Distribution	0.05	1 month
Trusted Messenger Strategic Storage	0.10	3 months
Partner Strategic Storage	0.20	2 months
Enhanced Strategic Storage	0.30	3 months

Table 3. Community interventions with their effectiveness and permanence.

Intervention	Effectiveness	Permanence
Screening	0.10	1 month
Caring Contacts	0.40	permanent
Low Touch	0.05	1 month
Trusted Messenger Gatekeeper	0.15	3 months
Enhanced Peer Support	0.20	3 months
Crisis Response Planning (CRP)	0.40	permanent

Determining Intervention Effectiveness Intervention-effectiveness parameters were derived from peer-reviewed literature on evidence-based suicide-prevention programs and adjusted through expert consensus to reflect expected real-world implementation effects (e.g., fidelity, comorbidities, etc.). For example, randomized trials of BCBT for suicide prevention have reported relative reductions in suicide attempts from ~60% to ~75% compared with standard treatment as usual therapy [16,17]. Within the model, these effectiveness rates are intentionally reduced, capped at approximately 55% to account for

implementation variability, dropout, and population heterogeneity. This more conservative calibration ensures projections remain plausible, reproducible, and transparent for decision-making applications.

Multi-Intervention Effect Logic It is possible that individuals may receive more than one intervention. The model applies the highest single intervention effectiveness rather than adding or multiplying effects. This approach is both pragmatic and clinically grounded. For example, if a veteran is screened for suicide risk (low effectiveness rate) and then receives a suicide-specific treatment such as BCBT (high effectiveness rate), the BCBT treatment effect replaces the earlier screening effect as the veteran undergoes BCBT. This prevents double-counting overlapping mechanisms and provides a conservative and likely more realistic estimate that reflects how care progresses in real-world settings.

Within the model, veterans who have not been treated with a permanent treatment are selected to go through these different interventions based on the capacity available for those interventions. They are taken from different distress levels based on the expected distribution for that specific intervention. These distributions are tied to both what intervention is appropriate for each distress level and who is being targeted for that intervention. For example, 10% of the available capacity for clinical CRP will treat low distress individuals, while 45% each will be used for moderate and high distress individuals. As another example, for Enhanced Strategic Storage, 40% of individuals will be from low distress, 50% from moderate distress, and 10% from high distress.

The clinical treatment pipeline starts with screening and distributes individuals based on capacity available and distress distribution for each treatment. The most complicated path is for Brief Cognitive Behavior Therapy (BCBT) (Figure 2).

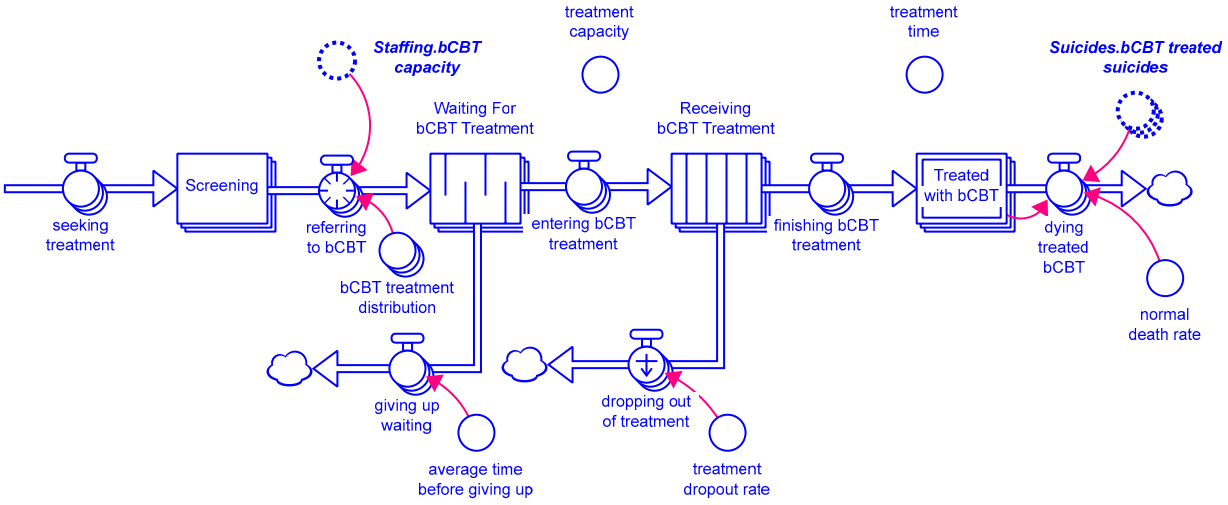


Figure 2. BCBT treatment path. Additional pathways from screening not shown.

As in the real-world, the model simulates screened individuals referred to BCBT treatment. If a clinician or clinic is currently at capacity, the individual must wait or may decide not to initiate treatment. Otherwise, they move into treatment. There is dropout from the roughly 14-week program, but all others complete the program successfully and are considered treated until they die, either from natural causes or by suicide.

Individuals can receive multiple interventions. For example, everyone who received BCBT was first screened for suicide risk. They may also have received a Crisis Response Plan (CRP). However, this does not mean that the total effectiveness is the sum of these interventions as the sum of the effectiveness of these combined interventions exceeds the maximum of 100%. After reviewing this potential issue with SMEs, it was decided that the intervention with the highest effectiveness is the final effectiveness for that person's

treatment. In addition, once an individual ends up in a permanent state (refer to Tables 1–3), they will not be treated with another intervention.

2.4. Capacity and Reach

In the beginning, we imagined the input to the model would be investment dollars and the model could determine capacity increases and veteran reach from that. Unfortunately, such a relationship does not exist. The Face the Fight grantees have different levels of existing capacity and different means to reach the veterans they serve. Instead, the veteran reach is calculated based on the grantees' expectations (and capacity adjustments). The model allows the reach to change every six months and linearly adjusts to each new reach over a two-month period. These numbers are updated by actual reach data from grant projects at the end of each grant period.

2.5. Lives Saved

To determine lives saved, the selected interventions have research demonstrating reductions in suicide behaviors. The VA reports the number of deaths by suicide each year with a consistent methodology. Suicide deaths are systematically underreported due to many factors including stigma, uncertainty in determining cause of death, insurance or legal reasons. SMEs determined an underreporting fraction (37%) based on currently available data, which gives us the total number of deaths by suicide [24]. Not all suicide attempts result in death; therefore, SMEs determined the probability of death by suicide as 10%. Dividing by the probability of death by suicide (10%), we estimate the number of suicide attempts that year:

$$attempts = (1 + underreporting\ fraction) \times deaths \div death\ probability \quad (1)$$

At this point, these attempts need to be distributed across the three distress levels. SMEs provided a suicide attempt distribution across these three distress levels: 4% low, 15% moderate, and 81% high. This then gives us the attempt rate by distress level. The number of deaths by suicide is then the number of attempts multiplied by the probability of death by suicide.

For each intervention, the attempt rate is reduced based on that intervention's effectiveness:

$$attempt\ rate = (1 - effectiveness) \times base\ attempt\ rate \quad (2)$$

For example, if a given intervention is 20% effective at reducing the attempt rate, the attempt rate for everyone treated with that intervention is 80% (100 − 20) of the untreated attempt rate. The number of lives saved is given by the number of deaths expected with no interventions minus the number of deaths expected with the chosen set of interventions:

$$deaths\ with\ intervention = Treated \times treatment\ attempt\ rate \times death\ probability \quad (3)$$

$$lives\ saved = deaths\ before\ interventions - \Sigma deaths\ with\ interventions \quad (4)$$

2.6. Feedback

Aside from the distress level backbone of the model, which has two major feedback loops, the model only contains minor feedback loops. Most of these are first-order controls on stock outflows. However, the model is part of a larger system with balancing feedback (Figure 3). Each year a new veteran suicide prevention report is released from the U.S. Veterans Affairs and new performance reports are received from the grantees. The SMEs review this data against what is already in the model and make recommendations for parameter changes. After the changes are integrated into the model, there is an iterative

back and forth with the SMEs to finetune the model parameters. We then use this new set of parameters for the next year.

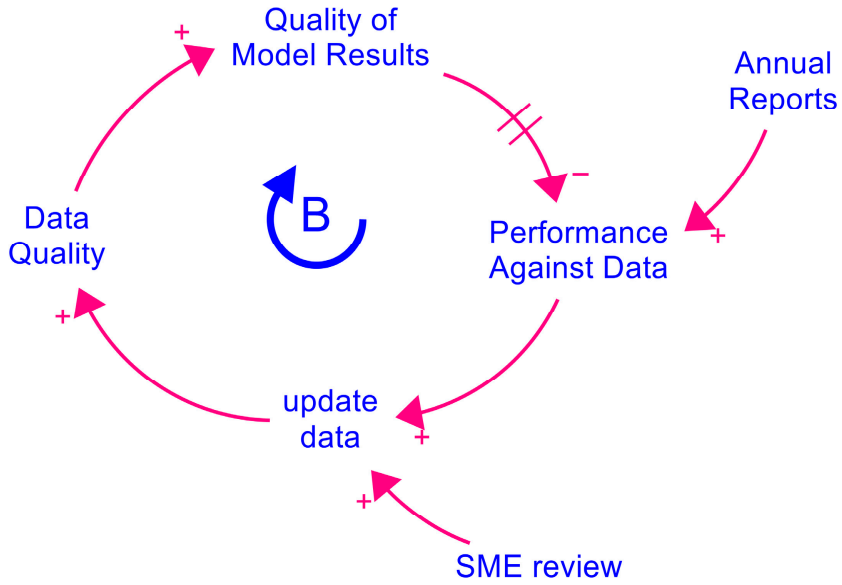


Figure 3. Annual data update balancing feedback loop.

3. Results

3.1. Investment Scenarios

There have currently been four 12-month grant rounds. Cohort 1 was funded from November 2022 through October 2023 and Cohort 2 was funded from October 2023 through September 2024. Cohort 3, a smaller round, was funded from spring of 2024 to spring of 2025. The fourth round started in October 2024 and will run through September 2025. Each grantee in each cohort projects their annual veteran reach for their current grant period, and SMEs calculate the expected reach for the nine-year duration of the Face the Fight program. These reaches are used by the model to calculate lives saved across 10 years (the year nine reaches are held constant in year 10). All results in this section represent modeled projections rather than direct observations. The model estimates population-level impact based on calibrated reach and effectiveness parameters derived from existing research and SME consensus.

Cohort 1 only included clinical programs, specifically clinical screening, clinical BCBT, and clinical CRP (Table 4). These interventions were not sufficient to reach the program goals over 10 years.

Table 4. Cohort 1 grantees' estimated annual veteran reaches.

Year	Screening	BCBT	CRP
1	15,000	2571	3724
2	30,000	3321	5724
3	45,000	4071	7724
4	60,000	4821	9724
5	75,000	5571	11,724
6	90,000	6321	13,724
7	105,000	7071	15,724
8	120,000	7821	17,724
9	135,000	8571	19,724

Cohort 2 increases the clinical intervention reaches (Table 5). However, capacity issues restricted large growth in these areas, so community programs were also added to the mix (Table 6). These include community screening, partner strategic storage, enhanced strategic storage, trusted messenger strategic storage, and community CRP.

Table 5. Cohort 1 plus Cohort 2 grantees' estimated annual veteran reaches.

Year	Screening	BCBT	CRP
1	15,000	2571	3724
2	27,784	2725	12,750
3	42,784	3270	15,300
4	57,784	3924	18,360
5	72,784	4709	22,032
6	87,784	5651	26,438
7	102,784	6781	31,726
8	117,784	8137	38,071
9	132,784	9764	45,686

Table 6. Cohort 2 grantees' estimated annual veteran reaches for community interventions. Abbreviations used in the header: SS: Strategic Storage, TM: Trusted Messenger.

Year	Screening	Partner SS	Enhanced SS	TM SS	CRP
1	0	0	0	0	0
2	99,162	1831	17,812	715	5638
3	118,994	2197	21,374	858	6766
4	142,793	2637	25,649	1030	8119
5	171,352	3164	30,779	1236	9742
6	205,622	3797	36,935	1483	11,691
7	246,747	4556	44,322	1779	14,029
8	296,096	5467	53,186	2135	16,835
9	355,315	6561	63,824	2562	20,202

Cohort 3 was a small midyear group of grantees, mostly clinical, which are shown at year 2.5 in Tables 7 and 8. Cohort 4 increases the clinical intervention reaches again (Table 7). Cohort 4 also increased the community fairly dramatically and added caring contacts (Table 8). In particular, community screening jumped from 100,162 to 345,162, a more than three-fold increase. This allowed community CRP, which has a 40% effectiveness, to grow from 5638 to 25,988 while strategic storage programs increased substantially.

Table 7. Cohorts 1–4 grantees' estimated annual veteran reaches.

Year	Screening	BCBT	CRP
1	15,000	2571	3724
2	27,784	2725	12,750
2.5	27,784	3864	18,662
3	44,558	6989	22,313
4	59,558	8387	26,776
5	74,558	10,064	32,131
6	89,558	12,077	38,557
7	104,558	14,492	46,268
8	119,558	17,391	55,522
9	134,558	20,869	66,626

Table 8. Cohorts 2–4 grantees' estimated annual veteran reaches for community interventions. Abbreviations used in the header: SS: Strategic Storage, Mess: Messenger.

Year	Screening	Partner SS	Enhanced SS	Trusted Mess SS	CRP	Caring Contacts
1	0	0	0	0	0	0
2	99,162	1831	17,812	715	5638	0
2.5	100,162	1831	20,812	715	5638	0
3	345,162	4331	33,312	6812	25,988	510
4	414,194	5197	39,974	8174	31,186	612
5	497,033	6237	47,969	9809	37,423	734
6	596,440	7484	57,563	11,771	44,907	881
7	715,728	8981	69,076	14,125	53,889	1058
8	858,874	10,777	82,891	16,950	64,666	1269
9	1,030,648	12,932	99,469	20,341	77,600	1523

3.2. Model Projections

Simulating the model for the set of interventions for Cohort 1 (Table 4) yields 1900 lives over 10 years (Figure 4, blue line). Adding the Cohort 2 interventions (Tables 5 and 6) in year 2 saves 4100 lives over 10 years (Figure 4, dashed red line). Adding the Cohort 3 and 4 interventions (Tables 7 and 8) saves 8100 lives over 10 years (Figure 4, dotted green line). To be clear, these are the number of lives saved through these interventions if all of our assumptions about intervention efficacy and suicide attempt rates are correct.

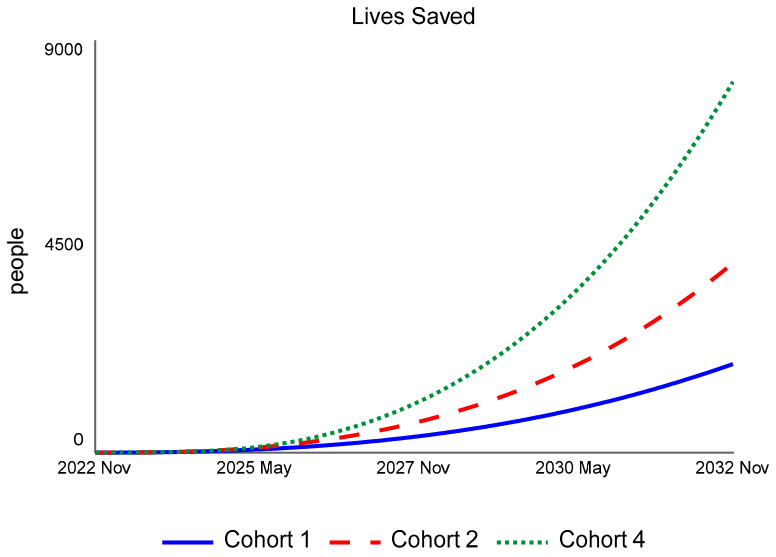


Figure 4. Lives saved after 10 years for Cohort 1 investments only (solid blue line), after adding the Cohort 2 investments in year 2 (dashed red line), and after adding Cohort 3 halfway through year 2 and Cohort 4 in year 3 (dotted green line).

Results highlight that portfolio-level gains are driven primarily by reach rather than marginal increases in individual intervention effectiveness. Community-level programs produce modest per-person effects but a large total impact due to population exposure.

3.3. Sensitivity Analysis

While the SMEs were generally conservative with intervention effectiveness relative to research and clinical trial results, the distribution of the population between low, moderate, and high distress is unknown. Likewise, the distribution of suicide attempts between these distress categories is unknown. While the actual probability of death by suicide from an

attempt is also unknown, the model first uses it to determine the suicide attempt rate by dividing and then multiplies attempts by it to calculate deaths by suicide, so it cancels out. The model is completely insensitive to it.

Testing the model's sensitivity to the population distribution and the suicide attempt distribution must be performed with care because when either distribution changes, the model has to be recalibrated to keep the fraction of the population in each distress category nearly constant when there are no interventions (a model assumption). Therefore, for each scenario tested, there is also a recalibration; i.e., the transition rates between distress categories are different for each scenario.

3.3.1. Testing the Sensitivity of the Population Distribution

Four scenarios were tested for the population distribution (Table 9). The first is the current model's distribution, while the second is the distribution from the first-year model. The other two scenarios test the effect of increasing or decreasing the percentage of high-distressed individuals. These were all tested with the additional Cohort 2 interventions.

Table 9. Population distress scenarios.

Case	% Low	% Moderate	% High
Base Case	73	23	4
Original	77	19	4
Fewer High	75	23	2
More High	71	23	6

The original distribution (Figure 5, dashed red line), which had fewer moderately distressed individuals (relative to the base case), showed more lives saved (3600) than the base case (Figure 5, solid blue line—3100). Halving the number of highly distressed individuals (Figure 5, dotted green line) saved more than twice as many lives (6500). Finally, increasing the number of highly distressed individuals by 50% (Figure 5, dot-dashed orange line) decreased the number of lives saved (2500). It is apparent that the model is quite sensitive to this parameter. Given this sensitivity, the SMEs reviewed it carefully and adjusted the distribution to the base case, which they felt was most realistic based on the best available data and SME consensus.

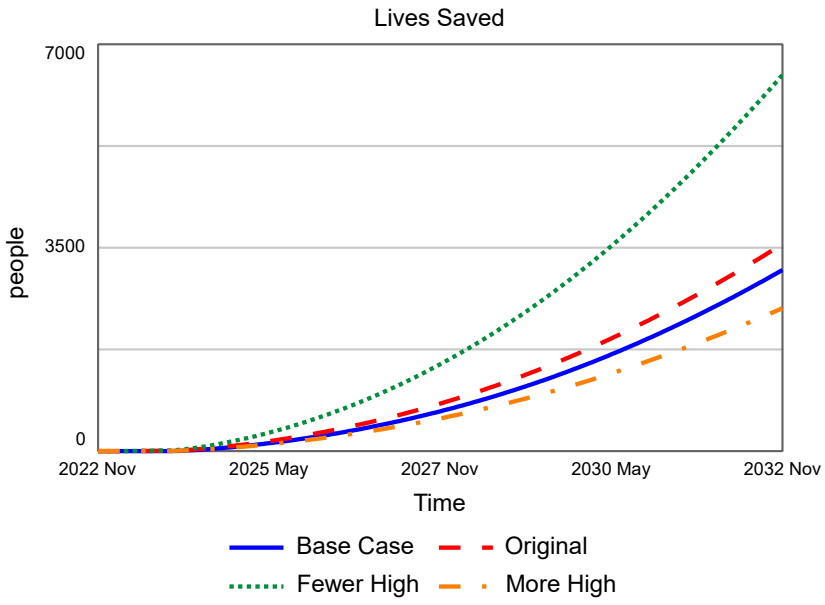


Figure 5. Lives saved sensitivity to the population distribution.

3.3.2. Testing the Sensitivity of the Suicide Attempt Distribution

Three scenarios were tested for the suicide attempt distribution (Table 10). The first is the current model's distribution, while the second is the distribution from the first-year model. The final scenario tests the effect of decreasing the percentage of high-distressed attempts. These were all tested with the additional interventions from Cohort 2.

Table 10. Suicide attempt scenarios.

Case	% Low	% Moderate	% High
Base Case	4	15	81
Original	1	9	90
Fewer High	10	20	70

It is not surprising that the original distribution (Figure 6, dashed red line), which had more high-distress attempts (relative to the base case), leads to more saved lives than in the base case (Figure 6, solid blue line—3100). Interestingly, decreasing the fraction of high attempts beyond the base case (Figure 5, dotted green line) did not have much impact (3200). There was a slight increase in lives saved, which can likely be attributed to the increased fraction of moderate-distress attempts. While the model is sensitive to this parameter, it seems to be most sensitive to very high values of the fraction of high-distress suicide attempts.

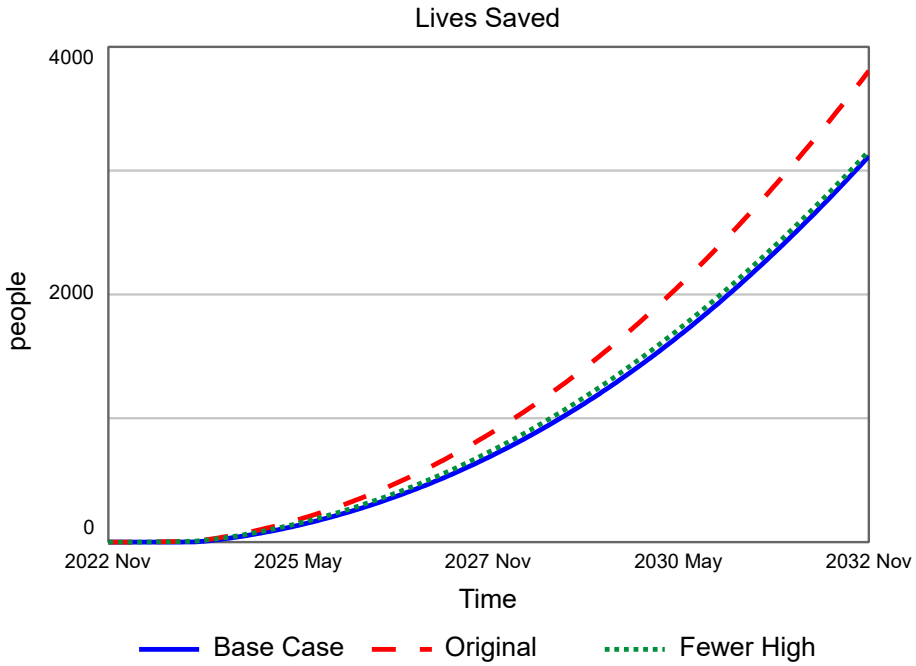


Figure 6. Lives saved sensitivity to suicide attempt distribution.

3.3.3. Testing the Sensitivity of Treatment Effectiveness

Because each treatment effectiveness multiplicatively reduces the suicide attempt rate for each treatment type, the number of lives lost to suicide within each treated group is proportional to one minus the effectiveness. In other words, when the effectiveness changes by 10%, we expect the number of lives lost within that treatment group to also change by 10%. To illustrate this, three scenarios were tested for the effectiveness of clinical CRP (Table 11). The middle one is the base case, with the first one 30% less than the base case and the last one 30% greater than the base case.

Table 11. Clinical CRP effectiveness scenarios.

Case	CRP Effectiveness
Lower	0.35
Base Case	0.50
Higher	0.65

In the base case (Figure 7, dashed red line), 62.4 lives are lost per month at the end of the simulation. When the effectiveness is reduced by 30% to 0.35 (Figure 7, solid blue line), lives lost per month increases 30% to 80.7. When the effectiveness is increased by 30% to 0.65 (Figure 7, dotted green line), lives lost per month decreases 30% to 43.9. The same holds for all of the effectiveness parameters.

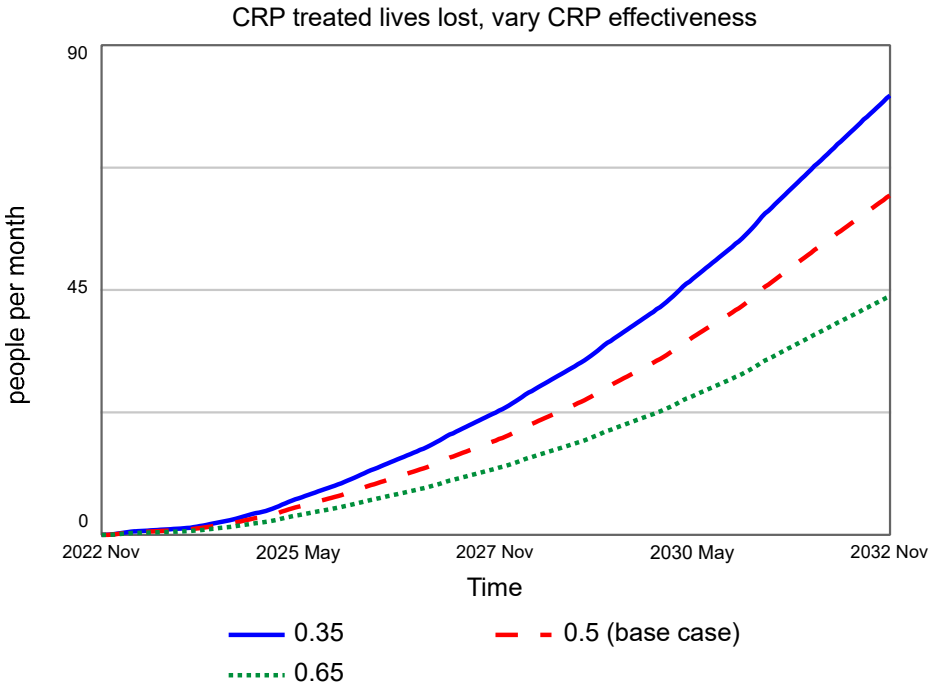


Figure 7. Lives lost despite clinical CRP treatment for varying CRP effectiveness.

3.4. Interpretation

Overall, modeled projections suggest that a balanced investment portfolio, combining clinical treatment, community engagement, and firearm-safety interventions, produces the greatest population-level impact on veteran suicide outcomes. Findings are intended to inform strategic investment and policy prioritization rather than predict observed counts. By emphasizing reach, realism, and annual recalibration, the model demonstrates how dynamic simulation can serve as a decision-support tool for large-scale suicide-prevention initiatives.

4. Discussion and Conclusions

One of the significant challenges in evaluating the impact of suicide prevention initiatives like Face the Fight is the inherent difficulty in quantifying lives saved and assessing the effectiveness of various interventions. The use of a system dynamics model, as described in this paper, provides a sophisticated approach to measuring both the estimated current and potential impact of these initiatives. This model represents a major advancement in understanding how different suicide prevention strategies interact and influence veteran suicide rates. By integrating peer-reviewed evidence, SME-calibrated parameters, annually

updated VA and grantee veteran data, and simulating various scenarios, the model serves as a dynamic and responsive tool that not only evaluates the effectiveness of existing interventions but also forecasts their potential future impact. Its ability to adapt and incorporate new data ensures that the model continues to evolve, offering ongoing insights into the most effective strategies for combating veteran suicide.

This model has been supportive in identifying which types and combinations of interventions may contribute most to overall suicide prevention goals. Clinical treatments such as Brief Cognitive Behavioral Therapy and Crisis Response Planning provide the greatest per-person reduction in suicide attempts, while community-based programs and firearm safety interventions generate larger population effects through greater reach. These insights guide more balanced funding strategies and demonstrate the complementary value of clinical and community approaches within Face the Fight's comprehensive prevention framework. This manuscript serves as a proof-of-concept application of the system dynamics model, illustrating how it can evaluate and forecast intervention impact using evidence-based inputs and SME-calibrated parameters. Because the model structure and logic are adaptable, it can also be generalized to other populations and public health contexts where multiple interventions interact to influence complex outcomes [8,9,25].

Another crucial insight from the model is its ability to highlight the risks of oversaturating specific interventions or exceeding capacity. For example, while BCBT is highly effective, the limited number of clinicians trained to deliver this treatment poses a challenge. If funding disproportionately favors BCBT without parallel investments in expanding clinician training, the system may become saturated, leaving many veterans without timely access to care. This finding suggests that an effective funding strategy should include a focus on capacity-building—such as training more clinicians—to ensure the system can meet the increased demand for services. Addressing these capacity issues is essential to ensuring that funding achieves the desired impact.

The flexibility of the system dynamics model also opens the door to expanding its application beyond the current set of interventions. For instance, while the current model does not explicitly stratify veterans by age, future iterations could integrate age distribution and life stage factors, particularly for veterans under 45, who represent a high-risk subgroup identified in VA reports, to refine the accuracy of projections. In addition, the model could be extended to capture the experiences of historically underrepresented groups within the veteran population, such as women, racial and ethnic minority veterans, and those living in rural areas, whose access to care and help-seeking behaviors may differ significantly. The model could also be adapted to assess the impact of broad public health campaigns designed to reduce stigma and encourage help-seeking behavior among veterans [1]. By inputting data on campaign reach and effectiveness, the model could simulate the long-term impact of these efforts on veteran suicide rates. Similarly, the model could be expanded to incorporate other suicide prevention initiatives, such as those implemented by the VA or other organizations, allowing for a more comprehensive assessment of the collective impact of multiple efforts.

Moreover, the model is not limited to the specific interventions currently funded by Face the Fight. It could be adapted to evaluate a wider range of interventions, including novel or emerging strategies in suicide prevention, both of which may be part of future grant awards in Face the Fight. This adaptability makes the model a valuable tool for exploring the potential effectiveness of innovative approaches before they are widely implemented. Furthermore, the model could be applied to other high-risk groups, such as first responders or individuals with chronic mental health conditions, by adjusting input parameters to reflect the specific characteristics and needs of these populations. The model's utility also extends to forecasting the potential future impact of interventions over a longer

timeline. By extending the time horizon, stakeholders can gain a clearer understanding of how current interventions may influence suicide rates over the next decade or beyond. Additionally, the model could simulate the effects of changes in external conditions, such as economic downturns or shifts in public policy, helping decision-makers prepare for and mitigate potential negative effects on at-risk populations.

Dynamic data models like this can serve as a public health planning tool that links research to policy. They can help decision-makers visualize impact under different investment scenarios, identify when interventions reach saturation, and coordinate prevention strategies across systems. Clinical programs such as Brief Cognitive Behavioral Therapy have high individual impact but limited scalability, while community approaches like screening or firearm storage can reach more people at lower intensity. It is not realistic that all high-risk veterans will access or even want intensive care, emphasizing the need for layered, cost-effective interventions. This framework can guide funding, workforce, and system-level policies to maximize population impact in veteran suicide prevention.

Overall, the system dynamics model developed for Face the Fight represents a significant advancement in veteran suicide prevention. It provides a robust framework for evaluating and optimizing existing interventions and offers the flexibility to expand its application to other interventions, populations, and scenarios. As the model continues to be refined and updated with new data, it holds the potential to guide future efforts in this critical area, ultimately saving more lives and improving the well-being of veterans and other at-risk groups.

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Appendix A. Model Equations

Stocks:

Distress:

$$High_Distress = \int (increasing_to_high + leaving_military_high_distressed - decreasing_to_moderate - dying_high)dt$$

$$Low_Distress = \int (leaving_military_low_distressed + decreasing_to_low - dying_low - increasing_to_moderate)dt$$

$$Moderate_Distress = \int (increasing_to_moderate + decreasing_to_moderate + leaving_military_moderate_distressed - increasing_to_high - decreasing_to_low - dying_moderate)dt$$

Suicides:

$$Suicide_Deaths = \int (increasing_deaths)dt$$

Treatment:

Comm_Screening[*Distress_Level*] = ∫(*starting_comm_screening*[*Distress_Level*]
− *treating_with_clinical_CRP*[*Distress_Level*] − *treating_with_comm_CRP*[*Distress_Level*]
− *treating_at_VA*[*Distress_Level*] − *leaving_comm_no_treatment*[*Distress_Level*])*dt*

Receiving_bCBT_Treatment[*Distress_Level*] = ∫(*entering_bCBT_treatment*[*Distress_Level*] −
finishing_bCBT_treatment[*Distress_Level*] − *dropping_out_of_treatment*[*Distress_Level*]*dt*

transit time(*Receiving_bCBT_Treatment*) = *treatment_time*

capacity(*Receiving_bCBT_Treatment*) = *treatment_capacity*

Receiving_Caring_Contacts[*Distress_Level*] = ∫(*entering_caring_contacts*[*Distress_Level*]
− *finishing_caring_contacts*[*Distress_Level*]
− *dropping_out_of_caring_contacts*[*Distress_Level*])*dt*

transit time(*Receiving_Caring_Contacts*) = *caring_contacts_treatment_time*

capacity(*Receiving_Caring_Contacts*) = *caring_contacts_capacity*

Receiving_Comm_Caring_Contacts[*Distress_Level*] =
∫(*entering_comm_caring_contacts*[*Distress_Level*]
− *finishing_comm_caring_contacts*[*Distress_Level*]
− *dropping_out_of_comm_caring_contacts*[*Distress_Level*])*dt*

transit time(*Receiving_Comm_Caring_Contacts*) = *caring_contacts_treatment_time*

capacity(*Receiving_Comm_Caring_Contacts*) = *comm_caring_contacts_capacity*

Screening[*Distress_Level*] = ∫(*seeking_treatment*[*Distress_Level*]
− *referring_to_bCBT*[*Distress_Level*] − *"treating_with_CRP/SPI"*[*Distress_Level*]
− *treating_with_lethal_means*[*Distress_Level*] − *leaving_no_treatment*[*Distress_Level*])*dt*

Self_referral_To_Treatment[*Distress_Level*] =
∫(*at_risk_noticing_distress_impacts*[*Distress_Level*] − *seeking_treatment*[*Distress_Level*])*dt*

Treated_Caring_Contacts[*Distress_Level*] = ∫(*finishing_caring_contacts*[*Distress_Level*] −
dying_caring_contacts[*Distress_Level*])*dt*

Treated_Comm_Caring_Contacts[*Distress_Level*] =
∫(*finishing_comm_caring_contacts*[*Distress_Level*]
− *dying_comm_caring_contacts*[*Distress_Level*])*dt*

Treated_Comm_Lethal_Means[*Distress_Level*] = ∫(*treating_comm_lethal_means*[*Distress_Level*]
− *losing_comm_lethal_means_impact*[*Distress_Level*])

Treated_Comm_Screened[*Distress_Level*] = ∫(*leaving_comm_no_treatment*[*Distress_Level*]
− *losing_comm_screening_impact*[*Distress_Level*])*dt*

Treated_Lock_Dist[*Distress_Level*] = ∫(*treating_lock_distribution*[*Distress_Level*]
− *losing_distribution_impact*[*Distress_Level*])*dt*

Treated_Low_Touch[*Distress_Level*] = ∫(*treating_low_touch*[*Distress_Level*]
− *losing_low_touch_impact*[*Distress_Level*])*dt*

Treated_Partner_Storage[*Distress_Level*] = ∫(*treating_partner_storage*[*Distress_Level*]
− *losing_partner_storage_impact*[*Distress_Level*])*dt*

Treated_Peer_Support[*Distress_Level*] = ∫(*treating_peer_support*[*Distress_Level*]
− *losing_peer_support_impact*[*Distress_Level*])*dt*

Treated_Screened[*Distress_Level*] = ∫(*finished_screening*[*Distress_Level*]
− *losing_screening_impact*[*Distress_Level*])*dt*

Treated_TM_Gatekeeper[*Distress_Level*] = ∫(*treating_TM_gatekeeper*[*Distress_Level*]
− *losing_TM_gatekeeper_impact*[*Distress_Level*])*dt*

Treated_TM_Storage[*Distress_Level*] = ∫(*treating_TM_storage*[*Distress_Level*]
− *losing_TM_storage_impact*[*Distress_Level*])*dt*

Treated_with_bCBT[*Distress_Level*] = ∫(*finishing_bCBT_treatment*[*Distress_Level*]
+ *comm_finishing_bCBT*[*Distress_Level*] − *dying_treated_bCBT*[*Distress_Level*])*dt*

Treated_with_Comm_CRP[*Distress_Level*] = ∫(*treating_with_comm_CRP*[*Distress_Level*] − *dying_treated_comm_CRP*[*Distress_Level*])*dt*
Treated_with_CRP[*Distress_Level*] = ∫(*"treating_with_CRP/SPI"*[*Distress_Level*] + *cross_treating_with_CRP*[*Distress_Level*] − *dying_treated_CRP*[*Distress_Level*])*dt*
Treated_with_CRP_at_VA[*Distress_Level*] = ∫(*treating_at_VA*[*Distress_Level*] − *dying_treated_at_VA*[*Distress_Level*])*dt*
Treated_with_Lethal_Means[*Distress_Level*] = ∫(*treating_with_lethal_means*[*Distress_Level*] − *dying_treated_lethal_means*[*Distress_Level*])*dt*
Waiting_For_bCBT_Treatment[*Distress_Level*] = ∫(*referring_to_bCBT*[*Distress_Level*] − *entering_bCBT_treatment*[*Distress_Level*] − *giving_up_waiting*[*Distress_Level*])*dt*

Flows:

Distress:

*decreasing_to_low = Transitions.medium_to_low_distress_rate*Moderate_Distress*
*decreasing_to_moderate = Transitions.high_to_medium_distress_rate*High_Distress*
dying_high = Suicides.distressed_suicides[*High*] *+ normal_death_rate*High_Distress*
dying_low = Suicides.distressed_suicides[*Low*] *+ normal_death_rate*Low_Distress*
dying_moderate = Suicides.distressed_suicides[*Medium*] *+ normal_death_rate*Moderate_Distress*
*increasing_to_high = Transitions.medium_to_high_distress_rate*Moderate_Distress*
*increasing_to_moderate = Transitions.low_to_medium_distress_rate*Low_Distress*
leaving_military_high_distressed = leaving_military_high
leaving_military_low_distressed = leaving_military_low
leaving_military_moderate_distressed = leaving_military_moderate

Suicides:

increasing_deaths = SUM(*distressed_suicides + screened_suicides + comm_screened_suicides + caring_contacts_suicides + comm_CRP_suicides + CRP_treated_suicides + bCBT_treated_suicides*) *+ lethal_means_suicides + additional_suicides*

Treatment:

at_risk_noticing_distress_impacts[*Distress_Level*] = *treatment_switch *capacity_utilization_clinical*desired_screening*
cross_treating_with_CRP[*Distress_Level*] = *community_treated_CRP*
dropping_out_of_caring_contacts[*Distress_Level*] =
    leakage outflow(*Receiving_Caring_Contacts*)
    leakage fraction = *caring_contacts_dropout_rate*
dropping_out_of_comm_caring_contacts[*Distress_Level*] =
    leakage outflow(*Receiving_Comm_Caring_Contacts*)
    leakage fraction = *comm_caring_contacts_dropout_rate*
dropping_out_of_treatment[*Distress_Level*] = leakage outflow(*Receiving_bCBT_Treatment*)
    leakage fraction = *treatment_dropout_rate*
dying_caring_contacts[*Distress_Level*] = *normal_death_rate*Treated_Caring_Contacts + Suicides.caring_contacts_treated_suicides*
dying_comm_caring_contacts[*Distress_Level*] = *normal_death_rate *Treated_Comm_Caring_Contacts + Suicides.comm_caring_contacts_suicides*
dying_treated_at_VA[*Distress_Level*] = *normal_death_rate*Treated_with_CRP_at_VA*
dying_treated_bCBT[*Distress_Level*] = *Suicides.bCBT_treated_suicides + normal_death_rate*Treated_with_bCBT*
dying_treated_comm_CRP[*Distress_Level*] = *normal_death_rate*Treated_with_Comm_CRP + Suicides.comm_CRP_suicides*

dying_treated_CRP[*Distress_Level*] = *normal_death_rate***Treated_with_CRP*
+ *Suicides.CRP_treated_suicides*
dying_treated_lethal_means[*Distress_Level*] = *normal_death_rate***Treated_with_Lethal_Means*
+ *Suicides.lethal_means_treated_suicides*
entering_bCBT_treatment[*Distress_Level*] = queue outflow(*Waiting_For_bCBT_Treatment*)
entering_caring_contacts[*Distress_Level*] = *treatment_switch***capacity_utilization_clinical*
**desired_caring_contacts*
entering_comm_caring_contacts[*Distress_Level*] = *treatment_switch*
capacity_utilization_community*desired_comm_caring_contacts*
finished_screening[*Distress_Level*] = *leaving_no_treatment* + *giving_up_waiting*
+ *dropping_out_of_treatment* + *dropping_out_of_caring_contacts*
finishing_bCBT_treatment[*Distress_Level*] = conveyor outflow(*Receiving_bCBT_Treatment*)
finishing_caring_contacts[*Distress_Level*] = conveyor outflow(*Receiving_Caring_Contacts*)
finishing_comm_caring_contacts[*Distress_Level*] =
conveyor outflow(*Receiving_Comm_Caring_Contacts*)
giving_up_waiting[*Distress_Level*] = queue outflow(*Waiting_For_bCBT_Treatment*)
purge after age = *average_time_before_giving_up*
leaving_comm_no_treatment[*Distress_Level*] = *starting_comm_screening*
− *CRP_treatment_flows*
leaving_no_treatment[*Distress_Level*] = *seeking_treatment* − *other_treatments*
losing_comm_lethal_means_impact[*Distress_Level*] =
Treated_Comm_Lethal_Means/time_to_lose_comm_lethal_means_impact
+ *Suicides.comm_lethal_means_suicides*
losing_comm_screening_impact[*Distress_Level*] =
Treated_Comm_Screened/time_to_lose_comm_screening_impact
+ *Suicides.comm_screened_suicides*
losing_distribution_impact[*Distress_Level*] =
Treated_Lock_Dist/time_to_lose_distribution_impact + *Suicides.lock_distribution_suicides*
losing_low_touch_impact[*Distress_Level*] =
Treated_Low_Touch/time_to_lose_low_touch_impact + *Suicides.low_touch_suicides*
losing_partner_storage_impact[*Distress_Level*] =
Treated_Partner_Storage/time_to_lose_partner_storage_impact
+ *Suicides.partner_storage_suicides*
losing_peer_support_impact[*Distress_Level*] =
Treated_Peer_Support/time_to_lose_peer_support_impact + *Suicides.peer_support_suicides*
losing_screening_impact[*Distress_Level*] = *Treated_Screened/time_to_lose_screening_impact*
+ *Suicides.screened_suicides*
losing_TM_gatekeeper_impact[*Distress_Level*] =
Treated_TM_Gatekeeper/time_to_lose_TM_gatekeeper_impact
+ *Suicides.TM_gatekeeper_suicides*
losing_TM_storage_impact[*Distress_Level*] =
Treated_TM_Storage/time_to_lose_TM_storage_impact + *Suicides.TM_storage_suicides*
referring_to_bCBT[*Distress_Level*] =
*bCBT_treatment_distribution***capacity_utilization_clinical***Staffing.bCBT_capacity*
seeking_treatment[*Distress_Level*] = *Self_referral_To_Treatment/time_to_seek_treatment*
starting_comm_screening[*Distress_Level*] =
*treatment_switch***capacity_utilization_community***desired_comm_screening*
treating_at_VA[*Distress_Level*] = *comm_to_VA*
treating_comm_lethal_means[*Distress_Level*] = *treatment_switch*
capacity_utilization_community*desired_comm_lethal_means*

treating_lock_distribution[*Distress_Level*] =
*treatment_switch*capacity_utilization_community*desired_lock_distribution*
treating_low_touch[*Distress_Level*] =
*treatment_switch*capacity_utilization_community*desired_low_touch*
treating_partner_storage[*Distress_Level*] =
*treatment_switch*capacity_utilization_community*desired_partner_storage*
treating_peer_support[*Distress_Level*] =
*treatment_switch*capacity_utilization_community*desired_peer_support*
treating_TM_gatekeeper[*Distress_Level*] =
*treatment_switch*capacity_utilization_community*desired_TM_gatekeeper*
treating_TM_storage[*Distress_Level*] =
*treatment_switch*capacity_utilization_community*desired_TM_storage*
treating_with_clinical_CRP[*Distress_Level*] = MIN(*effective_CRP_capacity*
− clinical_CRP_allocated, *desired_comm_to_clinical_CRP)*
treating_with_comm_CRP[*Distress_Level*] = MIN(*effective_comm_CRP_capacity*
− comm_CRP_allocated, *desired_comm_to_comm_CRP)*
"treating_with_CRP/SPI"[*Distress_Level*] = MAX(*CRP_treatment_distribution*
**capacity_utilization_clinical*Staffing.CRP_capacity − cross_treating_with_CRP*, 0)
treating_with_lethal_means[*Distress_Level*] = *lethal_means_treatment_distribution*
**capacity_utilization_clinical*Staffing.lethal_means_capacity*

Parameters and other variables:

Distress:
leaving_military_high_distressed = leaving_military_high
leaving_military_low_distressed = leaving_military_low
leaving_military_moderate_distressed = leaving_military_moderate
expected_fraction_distressed[*Low*] = 1 − *initial_moderate_fraction* − *initial_high_fraction*
expected_fraction_distressed[*Medium*] = *initial_moderate_fraction*
expected_fraction_distressed[*High*] = *initial_high_fraction*
fraction_distressed[*Distress_Level*] = *population_by_distress*/*Total_Population*
fraction_in_VA_treatment_end_state = 0.025
fraction_not_seeking_VA_care = 1 − *fraction_in_VA_treatment_end_state*
*Initial_High_Distress = initial_high_fraction*Initial_Subject_Veteran_Population*
initial_high_fraction = 0.04
Initial_Low_Distress = Initial_Subject_Veteran_Population
− (*Initial_Moderate_Distress* + *Initial_High_Distress*)
*Initial_Moderate_Distress = initial_moderate_fraction*Initial_Subject_Veteran_Population*
initial_moderate_fraction = 0.23
Initial_Subject_Veteran_Population
*= fraction_not_seeking_VA_care*Initial_Veteran_Population*
Initial_Veteran_Population = 18.8e6
leaving_military = leaving_military_per_year/months_per_year
*leaving_military_high = initial_high_fraction*leaving_military*
leaving_military_low = leaving_military − (*leaving_military_moderate* + *leaving_military_high*)
*leaving_military_moderate = initial_moderate_fraction*leaving_military*
leaving_military_per_year = 200000
normal_death_rate = (1/40)/12
population_by_distress[*Low*] = *Low_Distress*
population_by_distress[*Medium*] = *Moderate_Distress*
population_by_distress[*High*] = *High_Distress*

Total_Population = High_Distress + Low_Distress + Moderate_Distress

Suicides:
annual_attempt_rate_by_distress[*Distress_Level*]
= *annual_attempts_by_distress*/INIT(*Distress.population_by_distress*)
annual_attempts = annual_deaths/death_probability
annual_attempts_by_distress[*Distress_Level*] = *attempts_distribution*annual_attempts*
annual_deaths = (1 + *underreporting_fraction*)*base_annual_deaths*
attempt_rate_bCBT_treated[*Distress_Level*] = (1 − *bCBT_effectiveness*)*attempt_rate_by_distress
attempt_rate_by_distress[*Distress_Level*] = *annual_attempt_rate_by_distress/months_per_year*
attempt_rate_caring_contacts_treated[*Distress_Level*]
= (1 − *caring_contacts_effectiveness*)*attempt_rate_by_distress
attempt_rate_comm_caring_contacts[*Distress_Level*]
= (1 − *comm_caring_contacts_effectiveness*)*attempt_rate_by_distress
attempt_rate_comm_CRP_treated[*Distress_Level*]
= (1 − *comm_CRP_effectiveness*)*attempt_rate_by_distress
attempt_rate_comm_lethal_means[*Distress_Level*]
= (1 − *comm_lethal_means_effectiveness*)*attempt_rate_by_distress
attempt_rate_comm_screening[*Distress_Level*]
= (1 − *comm_screening_effectiveness*)*attempt_rate_by_distress
attempt_rate_CRP_treated[*Distress_Level*] = (1 − *CRP_effectiveness*)*attempt_rate_by_distress
attempt_rate_enhanced_peer_support[*Distress_Level*] =
(1 − *enhanced_peer_support_effectiveness*)*attempt_rate_by_distress
attempt_rate_lethal_means_treated[*Distress_Level*]
= (1 − *lethal_means_effectiveness*)*attempt_rate_by_distress
attempt_rate_lock_distribution[*Distress_Level*]
= (1 − *lock_distribution_effectiveness*)*attempt_rate_by_distress
attempt_rate_low_touch[*Distress_Level*]
= (1 − *low_touch_effectiveness*)*attempt_rate_by_distress
attempt_rate_partner_storage[*Distress_Level*]
= (1 − *partner_storage_effectiveness*)*attempt_rate_by_distress
attempt_rate_screened[*Distress_Level*] = (1 − *screening_effectiveness*)*attempt_rate_by_distress
attempt_rate_TM_gatekeeper[*Distress_Level*]
= (1 − *TM_gatekeeper_effectiveness*)*attempt_rate_by_distress
attempt_rate_TM_storage[*Distress_Level*]
= (1 − *TM_storage_effectiveness*)*attempt_rate_by_distress
attempts_distribution[*Low*] = 0.04
attempts_distribution[*Medium*] = 0.15
attempts_distribution[*High*] = 0.81
base_annual_deaths = 6392
bCBT_effectiveness = 0.55
bCBT_treated_attempts[*Distress_Level*]
= *attempt_rate_bCBT_treated*Treatment.Treated_with_bCBT*
bCBT_treated_suicides[*Distress_Level*] = *death_probability*bCBT_treated_attempts*
caring_contacts_effectiveness = 0.5
caring_contacts_suicides[*Distress_Level*]
= *caring_contacts_treated_suicides + comm_caring_contacts_suicides*
caring_contacts_treated_attempts[*Distress_Level*]
= *attempt_rate_caring_contacts_treated*Treatment.Treated_Caring_Contacts*

caring_contacts_treated_suicides[*Distress_Level*]
= *death_probability*caring_contacts_treated_attempts*
change_in_lives_saved = *lives_saved* − HISTORY(*lives_saved*, TIME, -1)
comm_caring_contacts_attempts[*Distress_Level*]
= *attempt_rate_comm_caring_contacts*Treatment.Treated_Comm_Caring_Contacts*
comm_caring_contacts_effectiveness = 0.4
comm_caring_contacts_suicides[*Distress_Level*]
= *death_probability*comm_caring_contacts_attempts*
comm_CRP_attempts[Distress_Level]
= *attempt_rate_comm_CRP_treated*Treatment.Treated_with_Comm_CRP*
comm_CRP_effectiveness = 0.4
comm_CRP_suicides[*Distress_Level*] = *death_probability*comm_CRP_attempts*
comm_lethal_means_attempts[*Distress_Level*]
= *attempt_rate_comm_lethal_means*Treatment.Treated_Comm_Lethal_Means*
comm_lethal_means_effectiveness = 0.3
comm_lethal_means_suicides[*Distress_Level*] = *death_probability*comm_lethal_means_attempts*
comm_screened_attempts[*Distress_Level*]
= *attempt_rate_comm_screening*Treatment.Treated_Comm_Screened*
comm_screened_suicides[*Distress_Level*] = *death_probability*comm_screened_attempts*
comm_screening_effectiveness = 0.10
CRP_effectiveness = 0.5
CRP_treated_attempts[*Distress_Level*]
= *attempt_rate_CRP_treated*Treatment.total_treated_with_CRP*
CRP_treated_suicides[*Distress_Level*] = *death_probability*CRP_treated_attempts*
death_probability = 0.10
distressed_attempts[*Distress_Level*] = *attempt_rate_by_distress*
*MAX(*Distress.population_by_distress* − *Treatment.treated*, 0)
distressed_suicides[*Distress_Level*] = *death_probability*distressed_attempts*
enhanced_peer_support_effectiveness = 0.2
lethal_means_effectiveness = 0.2
lethal_means_suicides = SUM(*lethal_means_treated_suicides* + *comm_lethal_means_suicides*)
lethal_means_treated_attempts[*Distress_Level*]
= *attempt_rate_lethal_means_treated*Treatment.Treated_with_Lethal_Means*
lethal_means_treated_suicides[*Distress_Level*] =
*death_probability*lethal_means_treated_attempts*
lives_saved = MAX(*base_suicide_deaths* − *Suicide_Deaths*, 0)
Note: *base_suicide_deaths* is the saved data from running the model with no treatment
lock_distribution_attempts[*Distress_Level*]
= *attempt_rate_lock_distribution*Treatment.Treated_Lock_Dist*
lock_distribution_effectiveness = 0.05
lock_distribution_suicides[*Distress_Level*] = *death_probability*lock_distribution_attempts*
low_touch_attempts[*Distress_Level*] = *attempt_rate_low_touch*Treatment.Treated_Low_Touch*
low_touch_effectiveness = 0.05
low_touch_suicides[*Distress_Level*] = *death_probability*low_touch_attempts*
partner_storage_attempts[*Distress_Level*]
= *attempt_rate_partner_storage*Treatment.Treated_Partner_Storage*
partner_storage_effectiveness = 0.2
partner_storage_suicides[*Distress_Level*] = *death_probability*partner_storage_attempts*
peer_support_attempts[*Distress_Level*]
= *attempt_rate_enhanced_peer_support*Treatment.Treated_Peer_Support*

peer_support_suicides[*Distress_Level*] = *death_probability*peer_support_attempts*
screened_attempts[*Distress_Level*] = *attempt_rate_screened*Treatment.Treated_Screened*
screened_suicides[*Distress_Level*] = *death_probability*screened_attempts*
screening_effectiveness = 0.15
TM_gatekeeper_attempts[*Distress_Level*]
= *attempt_rate_TM_gatekeeper*Treatment.Treated_TM_Gatekeeper*
TM_gatekeeper_effectiveness = 0.15
TM_gatekeeper_suicides[*Distress_Level*] = *death_probability*TM_gatekeeper_attempts*
TM_storage_attempts[*Distress_Level*]
= *attempt_rate_TM_storage*Treatment.Treated_TM_Storage*
TM_storage_effectiveness = 0.1
TM_storage_suicides[*Distress_Level*] = *death_probability*TM_storage_attempts*
underreporting_fraction = 0.37

Transitions:
high_to_medium_distress_rate = *normal_high_to_medium_distress_rate*
low_to_medium_distress_rate = *normal_low_to_medium_distress_rate*
medium_to_high_distress_rate = *normal_medium_to_high_distress_rate*
medium_to_low_distress_rate = *normal_medium_to_low_distress_rate*
normal_high_to_medium_distress_rate = 0.25/12
normal_low_to_medium_distress_rate = 0.000562968166781
normal_medium_to_high_distress_rate = 0.00375779213118
normal_medium_to_low_distress_rate = 0.02/12

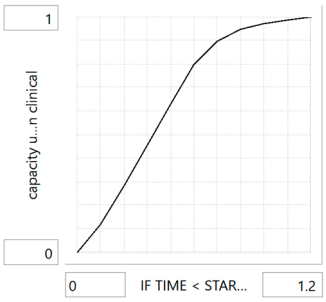
Treatment:
average_time_before_giving_up = 1
average_treatment_time = 3.375
bCBT_treatment_distribution[*Low*] = 0
bCBT_treatment_distribution[*Medium*] = 0
bCBT_treatment_distribution[*High*] = 1
capacity_utilization_clinical[*Distress_Level*] = *f*(IF TIME < STARTTIME + 6 THEN 100
ELSE *Untreated_Population//desired_treatment_clinical*):
(0.000, 0.000), (0.120, 0.120), (0.240, 0.282), (0.360, 0.455), (0.480, 0.629), (0.600, 0.798), (0.720, 0.897), (0.840, 0.948), (0.960, 0.972), (1.080, 0.987), (1.200, 1.000)
capacity_utilization_community[*Distress_Level*] = *f*(IF TIME < STARTTIME + 6 THEN 100
ELSE *Untreated_Population//desired_treatment*):
(0.000, 0.000), (0.120, 0.120), (0.240, 0.282), (0.360, 0.455), (0.480, 0.629), (0.600, 0.798), (0.720, 0.897), (0.840, 0.948), (0.960, 0.972), (1.080, 0.987), (1.200, 1.000)
caring_contacts_capacity = *Staffing.caring_contacts_capacity*caring_contacts_treatment_time*
caring_contacts_distribution[*Low*] = 0
caring_contacts_distribution[*Medium*] = 0.5
caring_contacts_distribution[*High*] = 0.5
caring_contacts_dropout_rate = 0.02
caring_contacts_treatment_time = 1
clinical_CRP_allocated[*Low*] = SUM(*treating_with_clinical_CRP*[*Medium*:*High*])
clinical_CRP_allocated[*Medium*] = *treating_with_clinical_CRP*[*High*]
clinical_CRP_allocated[*High*] = 0
comm_caring_contacts_capacity
= *Staffing.comm_caring_contacts_capacity*caring_contacts_treatment_time*
comm_caring_contacts_distribution[*Low*] = 0.2

comm_caring_contacts_distribution[*Medium*] = 0.7
comm_caring_contacts_distribution[*High*] = 0.1
comm_caring_contacts_dropout_rate = 0.03
comm_CRP_allocated[*Low*] = SUM(*treating_with_comm_CRP*[*Medium*:*High*])
comm_CRP_allocated[*Medium*] = *treating_with_comm_CRP*[*High*]
comm_CRP_allocated[*High*] = 0
comm_lethal_means_distribution[*Low*] = 0.4
comm_lethal_means_distribution[*Medium*] = 0.5
comm_lethal_means_distribution[*High*] = 0.1
comm_screened_crossover[*Distress_Level*]
= *crossover_switch*comm_screened_crossover_rate*starting_comm_screening*
comm_screening_distribution[*Low*] = 0.1
comm_screening_distribution[*Medium*] = 0.7
comm_screening_distribution[*High*] = 0.2
comm_to_VA[*Distress_Level*] = *seek_VA_treatment_distribution*desired_comm_to_CRP*
community_treated_bCBT[*Distress_Level*]
= SUM(*comm_LM_crossover_to_bCBT* + *comm_screened_crossover_to_bCBT*)
community_treated_CRP[*Distress_Level*] = *comm_LM_crossover_to_CRP*
+ *comm_screened_crossover_to_CRP* + *treating_with_clinical_CRP*
cross_treating_external_capacity_fraction = 1
CRP_treatment_distribution[*Low*] = 0.1
CRP_treatment_distribution[*Medium*] = 0.45
CRP_treatment_distribution[*High*] = 0.45
CRP_treatment_flows[*Distress_Level*] = *treating_at_VA* + *treating_with_clinical_CRP*
+ *treating_with_comm_CRP*
desired_caring_contacts[*Distress_Level*] =
*caring_contacts_distribution*Staffing.caring_contacts_capacity*
desired_comm_caring_contacts[*Distress_Level*]
= *comm_caring_contacts_distribution*Staffing.comm_caring_contacts_capacity*
desired_comm_lethal_means[*Distress_Level*]
= *comm_lethal_means_distribution*Staffing.comm_lethal_means_capacity*
desired_comm_screening[*Distress_Level*]
= *comm_screening_distribution*Staffing.comm_screening_capacity*
desired_comm_to_clinical_CRP[*Distress_Level*]
= *seek_clinical_CRP_distribution*desired_comm_to_CRP*
desired_comm_to_comm_CRP[*Distress_Level*]
= *seek_comm_CRP_distribution*desired_comm_to_CRP*
desired_comm_to_CRP[*Distress_Level*] = *screening_positive_rate*starting_comm_screening*
desired_lock_distribution[*Distress_Level*]
= *lock_dist_distribution*Staffing.lock_distribution_capacity*
desired_low_touch[*Distress_Level*] = *low_touch_distribution*Staffing.low_touch_capacity*
desired_partner_storage[*Distress_Level*]
= *partner_storage_distribution*Staffing.partner_strategic_storage_capacity*
desired_peer_support[*Distress_Level*]
= *peer_support_distribution*Staffing.enhanced_peer_support_capacity*
desired_screening[*Distress_Level*] = *screening_distribution*Staffing.screening_capacity*
desired_TM_gatekeeper[*Distress_Level*]
= *TM_gatekeeper_distribution*Staffing.trusted_messenger_gatekeeper_capacity*
desired_TM_storage[*Distress_Level*]
= *TM_storage_distribution*Staffing.trusted_messenger_strategic_storage_capacity*

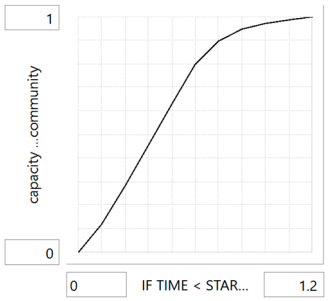
desired_treatment[*Distress_Level*] = *desired_TM_gatekeeper* + *desired_TM_storage*
+ *desired_caring_contacts* + *desired_comm_caring_contacts* + *desired_comm_lethal_means*
+ *desired_comm_screening* + *desired_lock_distribution* + *desired_low_touch*
+ *desired_partner_storage* + *desired_peer_support* + *desired_screening*
desired_treatment_clinical[*Distress_Level*] = *desired_caring_contacts* + *desired_comm_to_CRP*
+ *desired_comm_to_clinical_CRP* + *desired_screening*
effective_comm_CRP_capacity = SUM(*capacity_utilization_community*)
/SIZE(*Distress_Level*)*Staffing.suicide_management_capacity*
effective_CRP_capacity = SUM(*capacity_utilization_clinical*)/SIZE(*Distress_Level*)
Staffing.CRP_capacity
in_treatment[*Distress_Level*] = *treated* + *Waiting_Or_In_Treatment*
lethal_means_treatment_distribution[*Low*] = 0.1
lethal_means_treatment_distribution[*Medium*] = 0.5
lethal_means_treatment_distribution[*High*] = 0.4
lock_dist_distribution[*Low*] = 0.4
lock_dist_distribution[*Medium*] = 0.5
lock_dist_distribution[*High*] = 0.1
low_touch_distribution[*Low*] = 0.4
low_touch_distribution[*Medium*] = 0.5
low_touch_distribution[*High*] = 0.1
normal_death_rate = (1/40)/12
other_treatments[*Distress_Level*] = "*treating_with_CRP/SPI*" + *referring_to_bCBT*
+ *treating_with_lethal_means*
partner_storage_distribution[*Low*] = 0.4
partner_storage_distribution[*Medium*] = 0.5
partner_storage_distribution[*High*] = 0.1
peer_support_distribution[*Low*] = 0
peer_support_distribution[*Medium*] = 0.4
peer_support_distribution[*High*] = 0.6
screening_distribution[*Low*] = 0.1
screening_distribution[*Medium*] = 0.5
screening_distribution[*High*] = 0.4
screening_positive_rate = 0.2
seek_clinical_CRP_distribution[*Low*] = 0
seek_clinical_CRP_distribution[*Medium*] = 0.1
seek_clinical_CRP_distribution[*High*] = 0.2
seek_comm_CRP_distribution[*Low*] = 0.03
seek_comm_CRP_distribution[*Medium*] = 0.07
seek_comm_CRP_distribution[*High*] = 0.10
seek_VA_treatment_distribution[*Low*] = *0.02*
seek_VA_treatment_distribution[*Medium*] = 0.33
seek_VA_treatment_distribution[*High*] = 0.40
time_to_lose_comm_lethal_means_impact = 3
time_to_lose_comm_screening_impact = 1
time_to_lose_distribution_impact = 1
time_to_lose_low_touch_impact = 1
time_to_lose_partner_storage_impact = 2
time_to_lose_peer_support_impact = 3
time_to_lose_screening_impact = 1
time_to_lose_TM_gatekeeper_impact = 3

time_to_lose_TM_storage_impact = 3
time_to_seek_treatment = 0.5
TM_gatekeeper_distribution[*Low*] = 0.1
TM_gatekeeper_distribution[*Medium*] = 0.7
TM_gatekeeper_distribution[*High*] = 0.2
TM_storage_distribution[*Low*] = 0.4
TM_storage_distribution[*Medium*] = 0.5
TM_storage_distribution[*High*] = 0.1
total_treated_with_CRP[*Distress_Level*] = *Treated_with_CRP* + *Receiving_bCBT_Treatment*
treated[*Distress_Level*] = *treated_short_term* + *treated_long_term*
treated_long_term[*Distress_Level*] = *Receiving_bCBT_Treatment* + *Treated_Caring_Contacts*
+ *Treated_Comm_Caring_Contacts* + *Treated_with_CRP* + *Treated_with_CRP_at_VA*
+ *Treated_with_Comm_CRP* + *Treated_with_Lethal_Means* + *Treated_with_bCBT*
treated_short_term[*Distress_Level*] = *Treated_Comm_Lethal_Means* + *Treated_Comm_Screened*
+ *Treated_Lock_Dist* + *Treated_Low_Touch* + *Treated_Partner_Storage*
+ *Treated_Peer_Support* + *Treated_Screened* + *Treated_TM_Gatekeeper*
+ *Treated_TM_Storage*
treatment_capacity = *Staffing.bCBT_capacity***average_treatment_time*
treatment_dropout_rate = 0.01
treatment_switch = 0
treatment_time = *average_treatment_time*
Untreated_Population[*Distress_Level*]
= MAX(*Distress.population_by_distress* − *in_treatment*, 0)
Waiting_Or_In_Treatment[*Distress_Level*] = *Self_referral_To_Treatment* + *Comm_Screening*
+ *Receiving_Caring_Contacts* + *Receiving_Comm_Caring_Contacts*
+ *Receiving_bCBT_Treatment* + *Screening* + *Waiting_For_bCBT_Treatment*

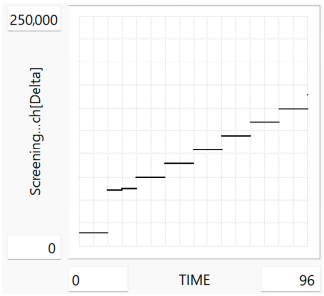
Graphical functions:
capacity_utilization_clinical: As we approach capacity, efficiency tapers off.



capacity_utilization_community: As we approach capacity, efficiency tapers off.



Staffing.Screening_Reach: Sample staffing function for Cohort 4. All staffing functions show the resources for that treatment over time.



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