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Understanding Mis-Implementation in U.S. State Health Departments: An Agent-Based Model

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Abstract

Introduction: The research goal of this study is to explore why mis-implementation occurs in public health agencies and how it can be reduced. Mis-implementation is ending effective activities prematurely or continuing ineffective ones, which contributes to wasted resources and sub-optimal health outcomes.

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Methods: The study team created an agent-based model (ABM) that represents how information flow, filtered through organizational structure, capacity, culture, and leadership priorities shapes continuation decisions. This ABM used survey data and interviews with state health department personnel across the U.S. between 2014 and 2020; model design and analyses were conducted with substantial input from stakeholders between 2019 and 2021. The model was used experimentally to identify potential approaches for reducing mis-implementation.

Results: Simulations showed that increasing either organizational evidence-based decision-making capacity or information-sharing could reduce mis-implementation. Shifting leadership priorities to emphasize effectiveness resulted in the largest reduction, while organizational restructuring did not reduce mis-implementation.

Conclusions: The model identifies for the first time a specific set of factors and dynamic pathways most likely driving mis-implementation, and suggests a number of actionable strategies for reducing it. Priorities for training the public health workforce include evidence-based decision-making and effective communication. Organizations will also benefit from an intentional shift in leadership decision-making processes. Based on this initial, successful application of ABM to mis-implementation, this work provides a framework for further analyses.

INTRODUCTION

The term *mis-implementation* refers to decision-makers ending effective activities prematurely (discontinuation mis-implementation) or continuing ineffective ones (continuation mis-implementation).[1] In a U.S. study, 36.5% of state health department (SHD) employees reported that programs often or always end that should have continued; 24.7% of respondents reported programs often or always continue when they should have ended.[2] Early termination of effective activities results in negative outcomes, including continued early onset or inadequate management of diabetes and other chronic conditions.[3] Continuation of interventions that are not effective in positively impacting intended priority population groups can exacerbate health disparities.[4,5]

Recent research provides nascent, suggestive evidence about factors related to mis-implementation.[1,2,6,7] The purpose of this innovative study is to build on previous work by using agent-based modeling (ABM) to gain insight into why mis-implementation occurs and what feasible approaches might reduce it.

ABM is a computational simulation methodology in which individual entities (e.g., employees), their behaviors, and the environments in which they operate are explicitly (and, typically, stochastically) modeled over time.[16] ABM has been increasingly utilized in guiding policy and practice in the social sciences in general and public healthspecifically.[17–26] There is also a growing body of evidence that ABM is particularly well-suited to studying organizations.[27–30] Until now, it has not been used to understand the complex and contextual drivers of SHD decision-making. Thus, this research serves as a first foray into the application of ABM to an important topic, specifically to: (1) develop an ABM with sufficient explanatory power to reproduce observed mis-implementation patterns; (2) use this ABM to explore counterfactual conditions to determine what feasible approaches might reduce mis-implementation frequency; and (3) consider how ABM could be further applied to explore drivers of and potential approaches to reducing mis-implementation.

Existing literature, supplemented by input from an Expert Advisory Group with domain and practical expertise, highlighted potential key determinants of mis-implementation. Following practices for participatory research, the team collaboratively identified factors within and external to public health departments that may drive occurrences of mis-implementation.[8–11] Four broad hypotheses emerged: (1) lack of evidence-based decision-making (EBDM), defined as “an approach to decision-making that combines the appropriate research evidence, practitioner expertise, and the characteristics, needs, and preferences of the community”[6]; (2) organizational culture that prevents leadership from having sufficient information about intervention effectiveness; (3) organizational structure that prevents leadership from having sufficient information about intervention effectiveness; and (4) internal and external pressures that induce leadership to make sub-optimal decisions by considering factors other than intervention effectiveness. These hypotheses are neither exhaustive nor mutually exclusive. The causal pathways potentially connecting all 4 to mis-implementation are likely to be intra-organizational in nature, may be bi-directional, may change over time, and might operate synergistically. To navigate obstacles introduced by the complex nature of these phenomena (i.e., heterogeneity, interdependence, and dynamic adaptation), an ABM research approach was used.[12–15]

METHODS

Model Design

Figure 1 depicts an ABM design aligned with characterizing and testing the hypothesized determinants of mis-implementation described above. It dynamically represents how information, filtered through organizational structure, capacity, culture, and leadership priorities, shapes decisions about whether to continue active interventions. Model design is summarized here and described in detail in the Appendix.

In the model, agents represent individual health department employees situated in a formal organizational structure, with overall organizational size, number of hierarchical levels, and number of employees per supervisor stochastically initialized. The organization has a set of active interventions, each with attributes representing age, evidence support for effectiveness given current implementation and context, and levels of support from external stakeholders and from funders. Agents have 2 attributes: EBDM ability and information-sharing propensity. EBDM ability reflects the accuracy with which an agent assesses the evidence support for intervention effectiveness for each active intervention; individual-level EBDM abilities collectively comprise organizational capacity for EBDM.[31–33] Information-sharing propensity reflects comfort with reporting these assessments to supervisors or adjusting their own assessment based on reports from supervisees; individual-level information-sharing collectively comprises organizational communication culture.

Each simulation run represents 36 months to reflect a combination of typical funding cycles, state health officer terms of office, and time periods for governmental public health organizations to make capacity building modifications.[31,34] At the start of each run, agents in the organization are initialized along with a set of current, active interventions. During each simulated month, agents' EBDM abilities can change, with employees' values gravitating toward those of their supervisors to represent personnel activities such as training, hiring, and retention. In any given month, employees might report their assessments of active interventions to their supervisors, with the probability that they do so based upon their current information-sharing values. Information-sharing values either increase or decrease based on whether agents' reports to supervisors result in adjustment of supervisors' assessments. Thus, information about interventions continuously flows from the lowest level of the organization to leadership, filtered through individual-level EBDM ability and information sharing propensity values.

Interventions are evaluated by leadership on an annual basis, with some probability that any given intervention will be reviewed off-cycle as well. Leadership makes continuation decisions based on their current assessments as well as interventions' other attributes. If an intervention is discontinued, it may be replaced by a new one. Except for age, for the sake of model parsimony intervention attributes are fixed during simulations.

Data Inputs Into Model

Parameter values for the baseline model condition were derived from 5 broad sources of data:

1. Three surveys of SHD employees conducted in 2014 (n=1,237),[2] 2016 (n=571),[35] and 2018 (n=643).[6] The outcome measures of perceived frequency of mis-implementation are from 2 samples of U.S. public health practitioners who completed cognitive response testing (n=12, n=11) followed by survey test-retest, 2–3 weeks apart (n=54, n=39).[1,6,36] Percent agreement of frequency responses of continuation and discontinuation mis-implementation in the 2 samples were 80.0%, 83.8% and 79.2%, 97.3%, respectively.[36] The questions in these 3 SHD surveys build upon previous studies of state and local public health practitioners with assessed reliability and validity.[1,6,36–39]
2. Semi-structured interviews with employees in 8 "case study" states conducted in 2019 (n=45).[1]
3. Supplementary stakeholder interviews conducted in 2020 with a set of participants with current or prior experience as directors of chronic disease units in SHDs (n=13). Questions were structured to solicit model input data (e.g., "On a scale of 1 to 10…how much are [intervention age] and [external support] related?").
4. Iterative feedback from an Expert Advisory Group.
5. ABM calibration to survey responses from 2014 and 2018 (described above) corresponding to the outcome of interest (mis-implementation frequency).

Table 1 summarizes how these data sources informed specific model elements.

Surveys and interviews were conducted and response data analyzed following protocols approved by the Washington University IRB.[1] Model parameterization details (including which measures from each source were used and how) are provided in the Appendix.

Analyses

Researchers assessed the ability of the model to reproduce observed fact patterns such as frequency of mis-implementation, given model inputs grounded in available real-world data (i.e., the baseline condition). The team then compared the baseline condition to mis-implementation frequencies produced by counterfactual scenarios representing approaches to reducing mis-implementation, varying organizational attributes or decision-making processes alone or in combination. Counterfactual conditions were selected with input from the Expert Advisory Group and based on findings from previous studies. They included:

1. Increased EBDM: representing an organization-wide shift in EBDM capacity, the parameter used to initialize agents' EBDM was increased by 10%, 30%, or 50%.[31,32]
2. Increased information-sharing: reflecting a shift in organizational culture and practices that makes transmission of and responsiveness to reports about assessed intervention effectiveness from employees to their supervisors, the parameter used to initialize agents' information-sharing propensity attributes is increased by 30% or 50%, applied either organization-wide or targeted at managers (i.e., the top three hierarchical levels).[40]
3. Organizational restructuring: keeping organizational size (i.e., the number of employees) consistent, organizations were made "taller" by increasing the parameter that initializes the number of hierarchical levels and reducing the one initializing the number of employees per supervisor, or "wider" by doing the inverse. Based on the relatively "tall" nature of real-world health departments at baseline, the model team considered 1 formulation of the former and 2 of the latter.[6]
4. Intervention continuation decision-making: representing a shift in training, incentives, protocols, and practices, the model considered scenarios in which leadership utilizes different criteria when making continuation decisions.[34,40,41] This set of scenarios was characterized as incremental removal of intervention age, stakeholder support, and funder support from continuation decisions. Thus, in the last case, decisions were made solely based on the department leader's assessment of intervention effectiveness.

Experimentation involved a full combinatorial sweep of the variations described above and stochastic repetition of runs under each condition to capture variation in organizations and interventions.[42]

RESULTS

First the study team compared model output under "baseline" condition to real-world reports of mis-implementation frequency. To compare categorical survey responses with continuous frequency outputs from the model, there were several simplifying assumptions. In Figure 2, the left and right panels (respectively) show the frequency with which ineffective interventions were continued (continuation mis-implementation), or effective programs were discontinued (discontinuation mis-implementation) when reviewed by leadership. The x-axes show frequency with which each type of mis-implementation occurs. The y-axis shows probability density, normalized for equivalent comparison between survey and model data. Categorical survey responses are shown with histogram bars, evenly distributed on the x-axes between 0 and 1 (e.g., with "never" placed between 0 and .2). Continuous model output values taken from 50 simulation runs, smoothed using a Gaussian kernel for ease of visual interpretation, are shown with solid lines. These comparisons are not intended as a formal test, but rather to qualitatively gauge the model's ability to broadly reproduce output patterns observed in the real world.[43] Overall, the model appeared capable of reproducing expected mis-implementation frequencies under baseline conditions.

Next, the team conducted counterfactual condition experimentation. Figure 3 depicts mis-implementation frequencies for each single change condition (i.e., those that differ from the baseline in only one respect), with the baseline mis-implementation frequencies shown for comparison. Across these scenarios, interventions were more likely to be discontinued than they were in the baseline condition. This tended to manifest itself as a reduction in continuation mis-implementation relative to baseline, but also, in many of the scenarios, a concomitant increase in discontinuation mis-implementation. From Figure 3, experiment effects fall into 4 broad categories:

1. Entirely negative: both types of mis-implementation increased relative to baseline. The very wide (an average of approximately 3 hierarchical levels and 14 employees per supervisor) scenario displayed this behavior, with average frequencies of each type of mis-implementation approximately 2 percentage points higher than baseline.

2. Net negative: continuation mis-implementation decreased less than discontinuation mis-implementation increased. The small (10%) EBDM increase scenario displayed this behavior, although impact on both types of mis-implementation (and thus the difference between them) was very small.

3. Net positive: continuation mis-implementation decreased more than discontinuation mis-implementation increased. The moderate (30%) and large (50%) organization-wide information-sharing increase, "tall" (an average of 6 hierarchical levels with approximately 4 employees per supervisor), and "somewhat wide" (an average of 4 hierarchical levels with 8 employees per supervisor) scenarios all displayed this behavior.

4. Entirely positive: both types of mis-implementation decreased. The other 7 scenarios displayed this desirable behavior. The reduction in continuation mis-implementation in scenarios where leadership did not include intervention age in their decisions was notable (an average reduction of over 20 percentage points), as were scenarios in which leadership also excluded other factors (i.e., external leadership or funder support) from their decision-making process; excluding both results in an average reduction of approximately 35 percentage points.

The Appendix contains specific values for outcome distributions depicted in Figure 3 and results from conditions where 2 or more of the experiment categories varied from baseline.

DISCUSSION

This research introduces a novel ABM of public health department organizational information flow dynamics and intervention continuation decision-making; within the constraints of available testing data, it demonstrates satisfactory explanatory power. Main results presented in Figure 3 suggest actionable strategies that align with existing literature and the experts' experiences. By identifying and operationalizing for the first time specific dynamic pathways driving mis-implementation, this model also serves as starting point for further efforts to inform and improve public health practice, as well as to guide future data collection.

Analysis of model results indicated that increasing organizational EBDM capacity tends to decrease mis-implementation frequency. This is not unexpected a priori, but the results quantify the strength of this relationship. EBDM helps public health departments identify the best available evidence about an intervention's potential impact given the context in which it will be deployed.[31–33] Emerging qualitative research on ending ineffective efforts highlights the importance of this capacity in reducing mis-implementation, as participants indicate that when successful, they leveraged evaluation data.[11,44] Findings also suggest that changes in organizational culture that facilitate information sharing can reduce mis-implementation, with that reduction more pronounced when changes are applied to the whole organization than to only management. In order to fully activate EBDM, employees must have "two-way street" relationships with their supervisors where they speak and are then heard.[11,45] When an employee is aware of a problem or has an idea, they must be comfortable sharing it with a supervisor, which is more likely to occur when that supervisor is open to the views of others, willing to reflect on and shift their own perspectives, and can help shepherd information that they receive into observable change.[11,46–49] Contrary to a priori expectations, changes in organizational structure (e.g., flattening the organizational hierarchies) did not consistently reduce mis-implementation.[6,7,50]

Following best practices in systems science, the study team incorporated sustained expert guidance, feedback, and engagement with ABM into the research plan.[12,16] Participants concurred that the results had face validity based on their experiences and intuition. One finding that not only has support from literature,[7,51] but particularly resonated with this group was that shifting decision-making processes to place additional emphasis on intervention effectiveness has the potential to dramatically reduce mis-implementation. An approach that effectively removed intervention age from leadership's continuation decisions was described as viewing them with fresh eyes, and approvingly seen as a way to remove organizational inertia and sunk cost mentality in favor of prioritizing effective interventions.[40]

ABMs are highly extensible, and the research reported here suggests ways to add sophistication in future iterations of the model. First, is exploration of additional formal and informal information sharing dynamics between employees within or between workgroups, allowing for consideration of arrangements such as matrix management and horizontal communication. Second, relevant decisions may be influenced by degree of centralization of public health activities in different states. Third, there is a need to explore alternative EBDM dynamics, such as peer-based or employee-led learning. Fourth, research is needed on the role of relative “implementability” of specific evidence-based interventions. Fifth, more information is needed on whether and how leadership might employ an option beyond continuation or discontinuation: e.g., adjusting intervention design or implementation targeting to improve effectiveness. Finally, in addition to iteratively improving this model, additional applications to exploration of how mis-implementation occurs—and might be addressed—at the local public health department level (with significant input from local-level partners) are envisioned.

The application of ABM to this important problem is highly innovative. This research presents an opportunity to extend beyond existing (often cross-sectional) efforts to improve organizational effectiveness, combining data from multiple sources to engage in thought experiments aided by computational simulation. Thus, without incurring costs associated with organizational initiatives or risking negative health outcomes from ineffective or counterproductive efforts, one can obtain valuable insights.

Limitations

The biggest challenge faced stemmed from limited previous research into mis-implementation, meaning there was a dearth of existing, relevant data to populate models. Previous work has shown that ABM can be a useful tool to advance the field in such circumstances.[52–55] This research effort identified the types of data that should be collected (along with when and how data should be gathered) to shed additional light on the causes of and solutions to mis-implementation. Specifically, future mis-implementation research will benefit from a validated measure of mis-implementation that does not rely on programmatic employees’ self-reported perceptions and longitudinal data describing intervention continuation patterns over time, as well as more detailed data on decision-making processes that result in continuation.

CONCLUSIONS

Mis-implementation has previously been defined and shown to be widespread with an important impact on public health—but neither the dynamic pathways that drive it nor the most effective ways to address have been well understood.[1–7] ABMs and similar computational modeling techniques have proven useful in public health because they examine the complex interplay among systems, organizations, community contexts, and individuals that influence population health, and extend beyond existing data to address counterfactual conditions.[12,22,56–60] The first-generation research presented here, along with related studies, suggests that 2 priorities for training in the public health workforce should be EBDM and effective communication, skills that are applicable to employees regardless of supervisory status.[11,32,61,62] Operationalizing insights gained from this research into leadership decision-making will require an intentional rethinking of how leaders are selected and trained and how they engage in decision-making processes: identifying and weighing priorities that might be in conflict as well as navigating relationships with stakeholders and funders to advocate for evidence-based continuation decisions.

In public health, one size often does not fit all. Computational modeling tools make it easier for decision-makers to select policies and practices that are likely to effect sustainable, positive change.[16,23,56] Tools to show context-relevant simulation output can help convey potential impacts and be useful springboards for informing specific recommendations. For example, ABMs that have been iteratively developed and applied have provided actionable guidance on selection of tobacco control policies such as menthol sales restrictions and retailer density reduction across communities.[23,24] This model might similarly shape recommendations to reduce mis-implementation in specific public health contexts.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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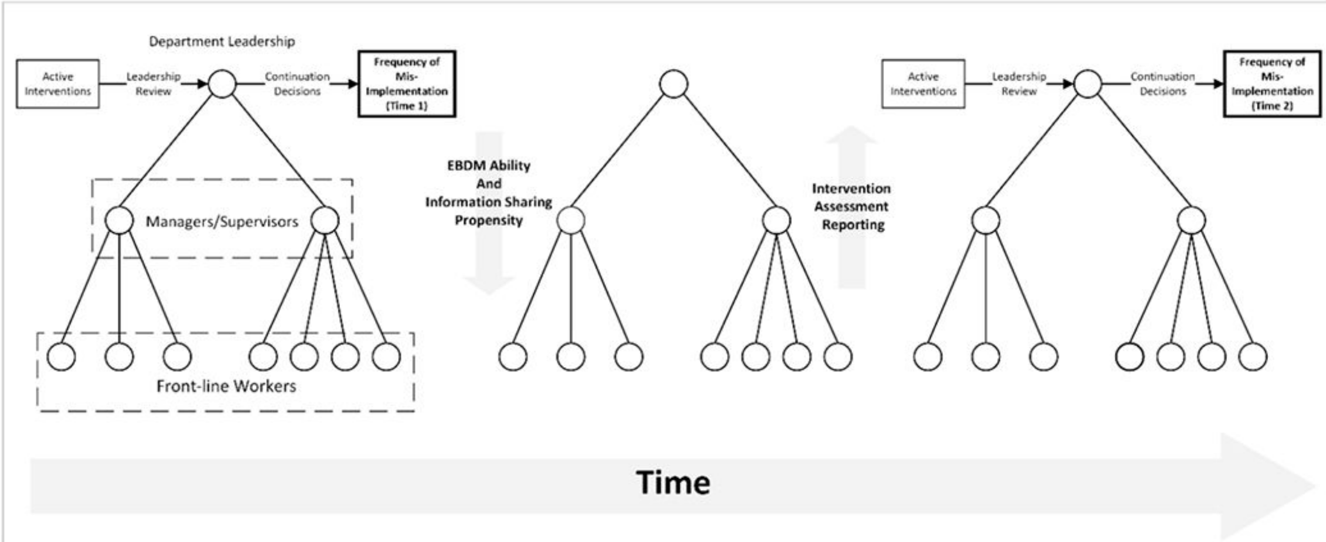

Figure 1.

Visual summary of model design.

Notes: Circles represent employees (agents) within a hierarchically structured organization, rectangles the organization-level set of interventions active at any given point in time, and grey arrows upward and downward interactions between agents that collectively comprise key organizational dynamics over time that drive the outcome of interest (mis-implementation frequency).

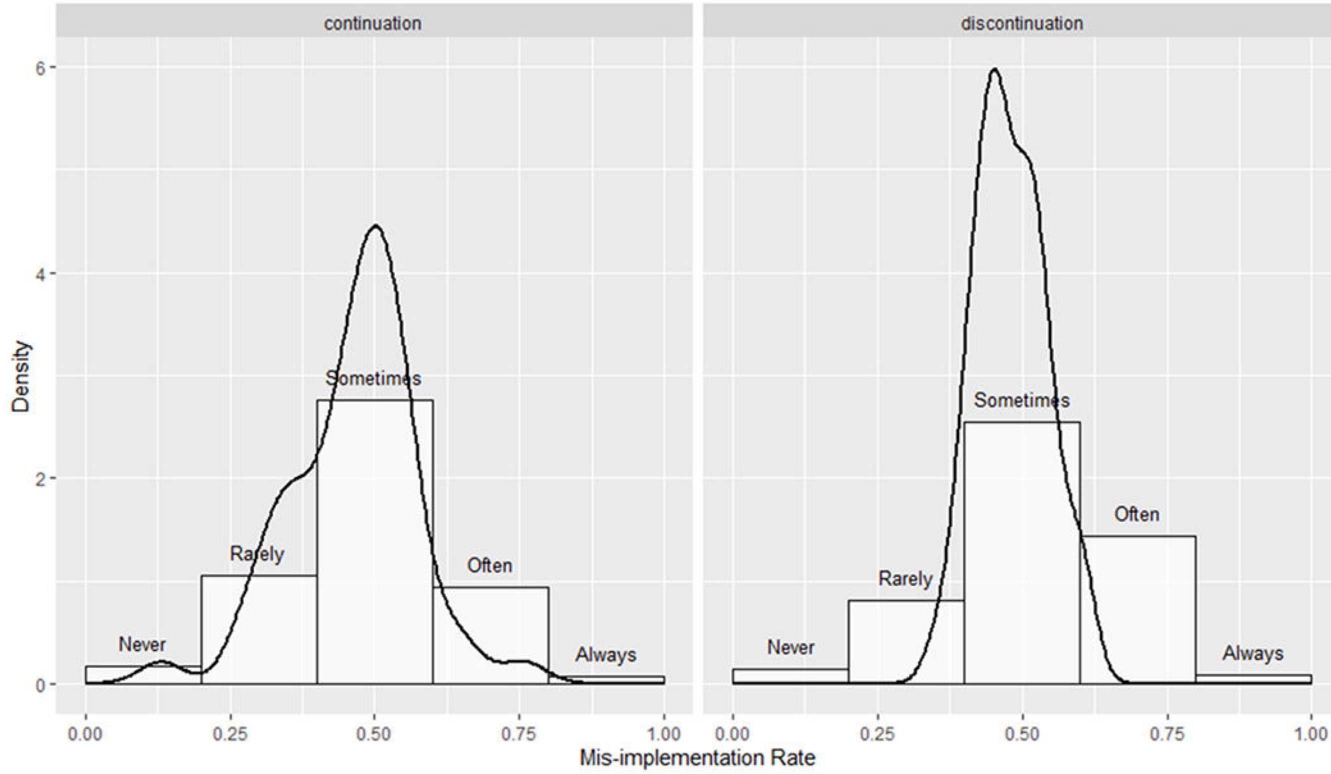

Figure 2.

Comparison of frequencies of mis-implementation from survey response data and model output.

Notes: The lines represent model output and the histogram bars depict frequencies of survey responses.

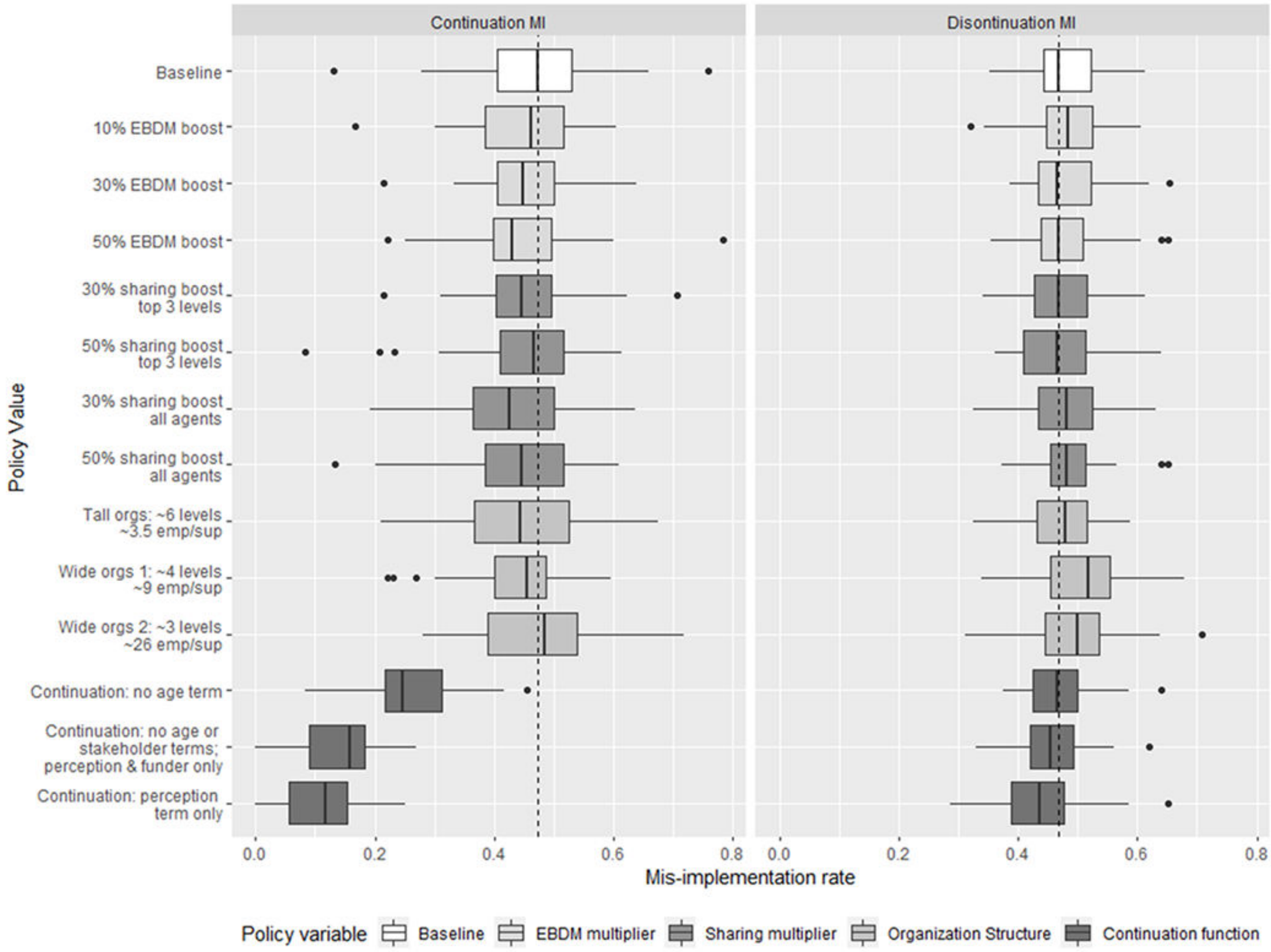

Figure 3.

Box-plot distributions of mis-implementation frequency.

Notes: Continuation of ineffective interventions or discontinuation of effective ones, respectively shown in the left and right panels, under the baseline as well as all “single intervention” policy value conditions. This includes “EBDM boost”—conditions in which agents are initialized with larger EBDM values, “sharing boost”—conditions in which agents are initialized with larger information sharing values, alternative organizational structures in which the organization is initialized such that it is either “wider” or “taller” than in the baseline condition, and conditions in which leadership utilizes different strategies for making continuation decisions. Median values are shown as vertical lines, the 25th and 75th percentile values as left and right box edges, 95% CIs as horizontal lines, and outlier values as dots. Frequency values are shown on the x-axis and the sole deviation from the baseline condition noted on y-axis (other than the baseline itself). For ease of comparison, the baseline median is presented as a dashed line.

Table 1.

Summary of Model Parameterization

Model element/Description of key parameters	**Data source**
Organizational structure	
Distribution used for number of organizational levels	Supplemental Stakeholder Interviews
Distribution used for number of supervisees assigned to supervisors	Survey Data
Active interventions	
Number of active interventions at start of run	Supplemental Stakeholder Interviews
Distribution used for initialization of intervention ages	Initial Stakeholder Interviews
Distributions used for initialization of intervention evidence support, external stakeholder support, funder support	Supplemental Stakeholder Interviews
Correlations between age, evidence support, external stakeholder support, funder support	Supplemental Stakeholder Interviews
Probability discontinued intervention is replaced with new intervention	Expert Advisory Group
Leadership review	
Probability of off-cycle intervention evaluation	Expert Advisory Group
Continuation decisions	
Continuation decision function terms	Model Calibration
EBDM ability	
Distributions used for agents' initial EBDM ability values	Survey Data
EBDM update magnitudes (upward or downward based on supervisor value; upward value is higher as it incorporates employee training)	Expert Advisory Group
Information sharing propensity	
Distributions used for agents' initial information sharing propensity values	Survey Data
Information sharing propensity update magnitude	Model Calibration
Intervention assessment reporting	
Report to supervisor probability function terms	Model Calibration
Assessment update probability function terms	Model Calibration
Assessment update magnitude	Model Calibration

EBDM, evidence-based decision-making.