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Model-driven decision support: A community-based meta-implementation strategy to predict population impact

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ABSTRACT

Purpose: Standard tools for public health decision making such as data dashboards, trial repositories, and intervention briefs may be necessary but insufficient for guiding community leaders in optimizing local public health strategy. Predictive modeling decision support tools may be the missing link that allows community level decision makers to confidently direct funding and other resources to interventions and implementation strategies that will improve upon the status quo.

Methods: We describe a community-based model-driven decision support (MDDS) approach that requires community engagement, local data, and predictive modeling tools (agent-based modeling in our case studies) to improve decision-making on implementing strategies to address complex public health problems such as overdose deaths. We refer to our approach as a meta-implementation strategy as it provides guidance to a community on what intervention combinations and their required implementation strategies are needed to achieve desired outcomes. We use standard implementation measures including the Stages of Implementation Completion to assess adoption of this meta-implementation approach.

Results: Using two case studies, we illustrate how MDDS can be used to support decision making related to HIV prevention and reductions in overdose deaths at the city and county level. Even when community acceptance seems high, data acquisition and diffuse responsibility for implementing specific strategies recommended by modeling are barriers to adoption.

Conclusions: MDDS has the capacity to improve community decision makers use of scientific knowledge by providing projections of the impact of intervention strategies under various scenarios. Further research is necessary to assess its effectiveness and the best strategies to implement it.

Abbreviations and acronyms: ABM, Agent-based modeling; AI, Artificial intelligence; CDPH, Chicago Department of Public Health; DDDS, Data-driven decision support; EMS, Emergency medical services; MDDS, Model-driven decision support; MOUD, Medication for opioid use disorder; NGO, Non-governmental organization; OTP, Opioid treatment program; PrEP, Pre-Exposure Prophylaxis.

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1. Background

Addressing community health issues requires collective action from multiple players. This makes decision making processes in these contexts uniquely complex. For example, preventing spread of and treating HIV requires multiple actors across several systems including public health, primary and specialty healthcare, and social services. However, data reporting from healthcare providers is mandated and responsibility for collecting data and coordinating prevention activities relies on a single entity, the government public health authority which uses funding and legal mandates to influence others to implement a rational community health strategy. In contrast, the response to overdose has been described as an ecosystem where no single entity is accountable for the outcome or the coordination of efforts [23]. There is no mandated data collection or standardized reporting. A community that wants to use data to drive decision making must combine data from multiple actors in different fields including public safety, public health, healthcare, education, behavioral health systems and social services. While the public health entity may be tasked with the responsibility of gathering and consolidating data and facilitating community intervention, it often does not and there is no federal mandate for it to do so. This multi-system perspective makes developing local strategy to reduce overdose deaths particularly challenging. Despite these challenges, communities have been encouraged to use a data driven decision support (DDDS) approach to address the overdose crisis in America [1,17,31]. In response, many communities have established overdose task forces with concerted efforts to track overdose deaths, and their relation to sociodemographic and relevant service data such as emergency medical services (EMS) calls, arrests, addiction treatment admissions, and hospital admissions [16,34].

While lacking a formal definition, data driven approaches are built on the foundational notion that better decisions can be made when evidence from data is used to support the decision-making process. In community public health, data driven decision making uses epidemiological data combined with evidence from clinical trials and other research studies that identify effective interventions for public health crises like the COVID-19 or HIV epidemics [11,19,32] and the overdose crisis.

DDDS requires analytic activities to summarize data over time and combine relevant findings from pertinent efficacy, effectiveness, and/or implementation research. This data aggregated and merged from multiple sources has the potential to describe how a community public health issue has evolved over time, the populations at risk, the service systems where individuals in need present, and geographic "hot spots". Presenting this information in easily understood formats such as dashboards can provide some guidance on what, whom, and where to target interventions.

Even if decision makers are well versed in the efficacy of various interventions and willing to apply only those interventions that have a good evidence base, decisions on how much of which evidence-based practice or policy to apply at any point in time in any given location are not easily made. Often, in lieu of actual scientific evidence, these decisions are made in response to other factors such as political expediency, availability of resources, by hearing what seems to be working in another community, or by applying for funding that is restricted to limited intervention choices.

Additionally, the paucity of implementation trials, particularly in the HIV [26] and substance use [4] field, mean that decisions made with clinical trial and local time dependent data cannot predict the size of impact as a function of the quality of implementation delivery of the intervention. These methods are also weak in examining how combined interventions are likely to behave. They provide limited information on how delivery of alternative interventions affects outcomes over time. Finally, they are of limited value in accounting for variation in impact across heterogeneous risk groups.

In sum, data, even when combined with deep knowledge of intervention effectiveness, generally does not provide sufficient insight into how best to intervene in community public health problems. Too often, decision makers find that their coalitions are routinely tracking what has happened in the past month, quarter, or year, but remain uncertain of how to act despite having access to rich local service and outcome data as well as lists of evidence-based interventions with research-based effect sizes. What seems to be missing are the steps that turn data into information and information into action.

Predictive modeling tools may prove to be that missing step. While predictive modeling has been cast into several different categorization schemes [13], we focus here on forecasting tools – those designed to help decision makers ask "what-if" questions and predict future outcomes under different scenarios. The choice of tools depends primarily on which analytic method is most suited to the need, but also on data availability and skills of the analyst. They can be as basic as regression or Markov models to understand the primary influencers of an outcome or as complex as the latest artificial intelligence (AI) data mining techniques.

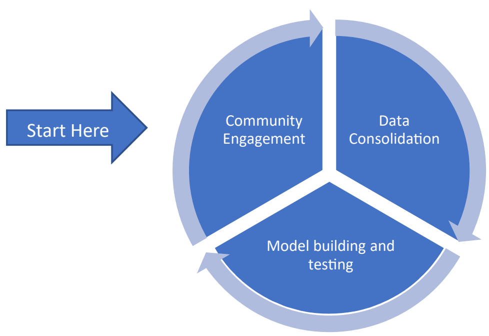
Agent-based modeling (ABM) is a stochastic simulation modeling tool where agents (people, things, organizations, systems) interact among themselves and with their environment within a computer simulation model, and can be used as a predictive modeling tool. Rather than simulating systemic trends, the trends in ABM emerge from agent interactions governed by behavioral rules that are based on theory and/or data [14,15]. Data are used as input for behaviors, but behaviors and contextual pressures can consequently be tailored or perturbed to see systemic impact over time. ABM for forecasting and health policy support has become more widely known during the COVID-19 pandemic when public health organizations simulated disease spread under various conditions [12,24]. In contrast to most other forecasting methods ABM has the potential to explore systemic trends, the underlying behavioral rules, and the ways in which they interact. Its flexibility in adjusting variables at different levels of the system make it a uniquely powerful tool for communities to test interventions before implementing them. Despite these affordances, in the context of overdose death prevention, the adoption of this methodology is extremely limited [2,29]. There is some work on simulation modeling within the context of HIV prevention that has explored the value of modeling for policy decision making support [7,30]. However, there has been very little use of predictive modeling for the overdose epidemic with only a few researchers developing models that while elegant have not been highly cited [20,8,9] or translated into decision making tools.

In this paper, we introduce model driven decision support (MDDS) as a meta-implementation strategy as it aims to inform decision making on a portfolio of implementation strategies through the use of three core elements: community engagement, data collection, and simulation model building. We define this as a meta-implementation strategy because it is distinguished by its absence of a specific evidence-based intervention(s) at the onset. The practices/policies that are implemented evolve out of the modeling results and discussions with decision makers. We posit this recursive, community-driven process as a strategy for implementing the use of modeling in decision making. Because the decision making is related to improving implementation of interventions, we refer to MDDS as a "meta-implementation strategy".

Our hypothesis is that local public health decision making can be improved via engaging decision makers in designing simulation models that address local needs. This process of local leaders and researchers co-developing simulation models with local data can provide the missing step that merges local data and clinical trial results into actionable information. Simulation modeling may lead to a recursive process whereby data collection, community trust and engagement with data and data-driven decision making are continuously improved. We showcase the application of MDDS through two case studies. These case studies illustrate the potential impact that simulation modeling may have on the selection of interventions to adopt, the informed distribution of resources, and trust in use of data for decision making. They also highlight some of the barriers to implementation of simulation modeling in this context.

2. Methods

We posit that there are three implementation pillars of model-based decision making in a community public health context: community engagement, data consolidation, and model building and testing. Community engagement is the entry point of a cyclical process that involves the three separate sub- processes.



Community-Based Model Driven Decision Support starts with community engagement.

Combined, these three sub-processes describe the community-based MDDS approach that provides guidance to the community and its decision makers on what interventions to apply, and potential implementation strategies that will yield the greatest results from those strategies taking into consideration the unique aspects of the local situation.

2.1. Community

Generally, there is a small group of leaders or decision makers responsible for addressing a specific community health need. Engaging these community groups in adopting predictive modeling as a decision support tool requires understanding of the decision-making processes, communication within and between organizations, and beliefs about the value and use of data. Understanding the perceived needs and potential constraints of community level decision makers is a pre-requisite for successful implementation of MDDS [21]. Engaging community groups effectively often necessitates the presence of a dedicated champion who can serve as the primary liaison between the modeling team and the community. Additionally, it is imperative that this champion and the broader community group members have the approval to actively participate and the necessary time to devote to the endeavor, in order to ensure they can authentically engage and guide the collaboration in an uninhibited manner.

Communities are already engaged in posing questions and prioritizing how best to use their limited resources to decide on which interventions and which implementation plans to provide. Predictive modeling may be introduced to the group by researchers who have linked with a local champion as described in our case studies, or may be initiated by interested public health entities or other community decision makers. Regardless of whether the instigator was internal or external, for modeling to be genuinely impactful in decision making, the community and modelers, living in their own separate cultural systems, need to establish a shared understanding and communication style that allows collaboration and compromise regarding what modeling can provide. Achieving this level of cultural integration, Stage III in cultural exchange theory [5], should facilitate communities in a) teaching modelers about how policy and program decisions are made, and b) posing questions that modelers respond to with predictions aptly suited for decision-making.

Working with established groups, such as public health entities combating HIV or community overdose task forces, allows model developers to participate in an existing process. The community determines what to prioritize by identifying what questions ABM or other predictive modeling tools should address, what data is made available to modelers and how model output will be used to make decisions. Community groups, like overdose task forces, often contain a fluid group of actors who may not be well organized and may not see themselves as a participant in creating a cohesive local vision. Individual actors have their own vision and priorities that they bring to the community group. The group dynamics shift as changes in membership evolve and beliefs in the value of data, even the validity of data, make working with community groups to incorporate MDDS into their process an ongoing experience in engagement. Modelers may have to function as facilitators to engage relevant parties to participate in shared planning and decision-making when groups are loosely formed and lack leadership or organizational structure. This ongoing community engagement is the starting point and foundational to the successful use of MDDS to address community public health issues that have multiple actors across multiple domains.

2.2. Data

To some extent, data necessary for simulation modeling of public health decisions is disease specific. A comprehensive ABM for HIV prevention would cover the following modules: demographics, intra-host epidemics, transmission mechanisms, treatment cascades, prevention and STI testing efforts, and social and mental health services, and intervention implementations; while a comprehensive ABM to address overdose deaths ideally covers the following modules: demographics, substance use point prevalence and dynamics, drug supply information, prevention efforts, health and substance use treatment system cascade [33], emergency services, interdiction activities including drug seizures, and social services such as housing, mental health care and other social supports. It also needs geographic data on locations of institutional and grass roots organizations, and on substance use and overdose sites. A functioning ABM would specify the interactions among these modules. These interactions include interorganizational processes such as the timing and probability of transitions between hospital emergency rooms and opioid treatment centers. Obtaining data with all these fields is often an arduous and time-intensive task. Community members may be reluctant to share sensitive data, making data access a challenge initially, as well as over time, as new actors replace existing data providers and data use agreements and privacy are revisited. Theoretically, as community members learn the value of MDDS, they may become more appreciative of the value of data sharing and less reluctant to share data that may add value to the MDDS process.

While recent research using ABM has published results assessing the effect of various factors on overdose or other opioid outcomes and identified targets for interventions [2,22] publications in research journals represent a point in time. As the problem has rapidly evolved, communities need to be able to model those changes in the environment as well as incorporating changes that are due to their previous efforts. For communities to use models for decision support, data must be frequently updated to be useful [29,30]. This has proven problematic for many communities, even those involved in research on data driven decision making for overdose prevention [10,34]. Data collection, cleaning, and sharing processes can all be time intensive. Concern for releasing reports that are inconsistent or premature due to incomplete data extends the time in each process. This is particularly true for government officials for whom the consequences of premature release of incomplete data can be severe.

2.3. Model building

Ensuring modeling experts understand community priorities and how existing data can be used to answer relevant questions requires an iterative process which includes both the modeling expert and community partners. A collaborative iterative process that starts from a simple model, basic simulation experiments, and sharing the results with community decision makers for the purpose of feedback and discussion, leads to follow-up questions and identifies additional data needs. As community members become more familiar, their requests of the model add complexity with interacting interventions and environmental changes. This process increases awareness in the community of how such models can be used to answer relevant questions and inform decision making. It increases ownership of and trust in the eventual modeling process being created, which results in an increasingly comprehensive model with greater breadth allowing for the answering a wider range of questions. This process is essential in establishing the trust that allows individual actors to accept and act on recommendations based on the model.

As the model building process is cyclic and model expansion generally occurs gradually it is crucial to ensure that models are built in modular fashion [28]. This is especially relevant as model complexity should increases over time. In a modular model each dynamic, system, or behavior is encapsulated in its own section, which takes a pre-defined input (dataset, value) and produces a pre-defined shape of output. Such a structure ensures that a module can be changed/replaced/added without the risk of breaking the overall model.

As the model evolves based on community input and answering locally relevant questions in the process, communities develop greater experience and trust in the value of using MDDS. Additionally, they develop a deeper understanding and ability to recognize the inferences that their data provides resulting in a more intentional use of their data to assess the impact of their interventions in addition to asking "what if" questions using ABM.

2.4. Evaluating implementation of MDDS

Assessing the utility of a meta-implementation strategy, requires evaluating the implementation of that meta-implementation strategy itself. In terms of evaluating MDDS wholistically, we have chosen to use the Stages of Implementation Change (SIC) tool [3,25], so we can examine how well each of the three elements of the system is proceeding and identify where barriers to adoption exist. SIC is a process evaluation tool that standardizes implementation stages [3]. While SIC stages are universal, the identifiers of completion are specific to the practice being implemented.

Indicators of completion for first three phases of model-based decision support system implementation.

SIC stage	Community	Data	Model Building
Engagement	Form and extend coalition	Agreement to share data	Demographics
	Specify goals	Sharing data	Geocoding
	Identify champion and partner with research team	Adequate frequency of data updating	Drug related outcomes
	Sustainable staff/ funding	Data linkage	Services effects
Consideration of Feasibility	Prioritize potential intervention options	Availability of timely administrative data	Represent implementation strategies
	Identify resources and limitations		Produce and display simulation results
	Understand perception of community members	Assessment of costs and resources	Examine impact sensitivity to resource allocation
Readiness Planning	Presentation of simulations and optimal solutions	Identify additional data sources	Prepare written summaries of findings
	Investigate obtaining additional data	Permission to seek additional data	Identify ways in which model can be improved

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Two case studies, one ongoing (Pinellas, overdose), the other complete (Chicago, HIV) are presented to demonstrate the process of implementing MDDS as a meta-implementation strategy that supports community-level decision making in what and how to implement strategies to address public health issues. We use the HIV case study as an example of a completed effort upon which the ongoing overdose study is modeled.

3. Results

3.1. Case Study #1

Pinellas County, Florida is an urban county, with a population density of 3425 people per square mile, the highest density in Florida. It had an overdose death rate of 61 per 100,000 in 2022, the most recent year published [6]. An opioid task force that involves as many as 200 community members in each quarterly meeting has been meeting since June, 2017. A grant from the Bureau of Justice Assistance supported the development of a multi-party data lake and a substance use data dashboard for the county.

Pinellas County already had a coalition that included participants from multiple sectors including public health, county government, EMS, the medical examiner, treatment providers and law enforcement. The co-chairs of the task force welcomed the research team and introduced the concept of ABM to the rest of the task force. The task force meeting began holding a standard agenda item for a report on modeling activities in the first meeting after the introduction of the concept to the co-chairs. Task force leadership engaged in discussions with the research team regarding priority questions/issues to simulate. Goals and milestones in the community process were easily achieved. For these reasons, Pinellas County currently fits into the readiness planning stage in the SIC model in the community bucket.

From a data perspective, there was already a data use agreement for the task force members and the ABM project was added to the existing agreement after one meeting of task force leadership and agreement from the signatories. However, technical data sharing process issues led to some delays in using the data for ABM. First, because the work was done under the aegis of a research grant, IRB approval was sought. Since the proposal involved using HIPAA protected data and research teams at two universities, the study required full IRB review which took three months to achieve. Additionally, to protect the patient identifying information, access to secure data storage locations required an approval process and identification of computers to be used for remote data access. These technical issues, some of which were specific to research and would not be issues otherwise, added about six months to the pre-implementation period. Data also needed to be cleaned and reformatted for use in NetLogo [27], the ABM tool. This would place the county in the SIC category of consideration of feasibility in the data process.

The first simulation experiment examined location and quantity of naloxone distribution. There was much concern expressed in two task force meetings regarding specific businesses being unwilling to have naloxone available on their premises. The research team agreed to run a series of simulation experiments that involved adding new locations for distribution and testing the effect of various levels of increased availability of this overdose reversal medication in the county. The simulations demonstrated very small effects for either increasing the quantity of naloxone available or for targeting the location of availability to areas that seemed to lack it. The research team added a simulation that increased the number of people who used illicit substances in the presence of another person with naloxone available rather than using alone. This model showed the greatest change in effect. The task force seemed interested in these initial findings, but unsure what to do with them, though they did stop expressing frustration with specific business' refusal to stock naloxone on site. Lack of interest led modelers to not run simulations on strategies to ensure people did not use alone. In addition, this result further emphasizes the importance of creating actionable information from the data collected. The development of a model that addressed a community question without further exploration or engagement on the results of the modeling experiment put the community in the engagement stage of the SIC for model building.

Further simulations were run in response to questions regarding methods of increasing availability of medication for opioid use disorder (MOUD). Results were provided that demonstrated that adding two new proposed opioid treatment programs (OTPs) would have the largest effect compared to other proposed strategies. This result was surprising to task force members who raised questions about assumptions regarding efficacy in terms of how different OTPs function. Modeling results generated discussion about the data and other model inputs, increasing engagement, but not necessarily trust in using modeling as a tool.

The final simulation to date included results of a strategy that combined increased naloxone distribution, reduced solitary substance use, and increased treatment availability. The results of this simulation experiment demonstrated the additive effect of multiple interventions. This outcome generated discussion regarding using modeling as a tool to make decisions regarding abatement fund expenditures and how to ensure decision makers for that specific new funding would have access to the results. The timing of the abatement committee decisions and the role of the task force in providing input into those decisions may have increased the interest of the task force members in the utility of MDDS. In this example, three rounds of running simulations based on community identified concerns led to an awareness of the potential utility of predictive modeling in their decision process.

Use of MDDS subsequently appeared in the task force strategic plan. How community organizations will incorporate findings from ABM experiments in response to community questions is still an unknown. While the task force as a group has expressed interest in using ABM and in the results of initial experiments, how individual organizations use the results in their planning and quality improvement activities remains unknown at this writing. Restructuring of task force leadership is underway to assist bringing in the necessary voices to carry out strategic plan objectives, therefore, ABM is highly anticipated to be utilized after these changes are in place.

There are two next steps of our agent-based model building in Pinellas County. The first will examine what changes in proximal intervention targets are needed to have an impact across time on the target outcome, overdose deaths. We consider proximal intervention targets to include NIH's four pillars of prevention, harm reduction, treatment, and recovery. Examples of proximal indicators of these factors include the numbers of new users, number of EMS calls, number of users who are newly linked to treatment, and those who are retained in care. Once these targets are identified, we can model the level of change of these proximal outcomes that will achieve a targeted change in overdose deaths. This approach is examined in detail in recent work on eliminating HIV infections [30] described below. In this way, we can link strategy with easily measured proximal outcomes and distal outcomes that are the primary goal.

The second future step of MDDS in Pinellas County is to examine what combinations of interventions and implementation strategies, are needed to achieve the community's overdose reduction goal. For this second step, we simulate what combinations of interventions, and how different implementation strategies can achieve the impact on the proximal target outcomes necessary to meet the stated overdose reduction goal. We describe a similar process in Case Study 2.

The work with Pinellas County is still underway. Significant challenges have required a rededication to the collection and compiling of data sources leveraged in the modeling. While certain information is available through the data lake, other necessary elements require ongoing coordination with local stakeholders that has been lost due to staff transitions, delaying the ability of the modeling team to run simulation experiments with more current data. Recent changes in leadership at the task force level and in key actor positions in community organizations may impact progress in either a positive or negative direction. These issues are to be expected in a community level implementation of any intervention and the time to address them needs to be included in expectations.

3.2. Case Study #2

Within the context of HIV prevention in Chicago we have seen evidence of MDDS impacting decision making, albeit with a smaller group of actors. Here we worked with a single partner, the local Chicago Department of Public Health (CDPH) to provide guidance on how to best attain the goals set forth in their getting-to-zero plans, i.e., reduce HIV incidence by 90% by 2030. In an ongoing process we built and tailored a high-fidelity ABM capturing the behaviors among men-who-have-sex-with-men (MSM) in Chicago, in line with their local priorities. Then, based on input from our partners, six levers of change were identified. Three focused on prevention (PrEP) and three on treatment activities in the care system, roughly aligning with linkage, retention and efficacy of each of the respective services, to provide guidance on where to focus intervention efforts.

Using data from 1) the census to inform our population and spatial distributions, 2) from CDPH to inform care activities, and 3) from RADAR [18] a local longitudinal cohort to inform sexual networks, we aligned the model to specifically capture local dynamics which we would consequently validate using our partners local expertise, ensuring validity of the inputs to the model. Next, we validated the modeled system-level outcomes. As the model was built using 2015 data, we checked if modeled outcomes matched observed outcomes in 2016, ensuring the model accurately captured systemic trends.

In the next stage we used the model to explore a wide range of what-if scenarios, effectively showing the predicted progression of the HIV cascade for the next 15 years under multiple combinations of perturbations in the six levers of change. Key insights from these simulation experiments included 1) a quantification of how hard it would be to attain the getting-to-zero goal, 2) an understanding of the combination of interventions needed to achieve such a goal, 3) the realization that a status neutral approach would be required, 4) an evaluation of the recent efforts relative to desired impact, and 5) the understanding that disparities will not be resolved without tailored efforts [29,30]. Such insights were then used to start a much better-informed conversation about increasing intervention impact and has since guided local decision making. Furthermore, it has spurred an ongoing dialog with our partners resulting in a new cycle of planned model adaptations in line with the new what-if questions that arose during our interactions.

4. Discussion

Predictive modeling tools are under-utilized for decision support in the public health sphere. This is often because decision making responsibility is diffuse, data is inadequate or skills/knowledge of how to use predictive modeling tools is unavailable. Use of these tools may be a critical missing step between data and action. This is particularly cogent in the effort to address overdose deaths as they have continued their 20 + year trajectory of increasing incidence. The more than doubling of the federal resources since 2016 that are aimed at this issue seemingly has had little impact. As communities receive funding from federal and state government and the opioid abatement settlement, they look to lists of evidence-based practices to know what to do and discuss how to prioritize services based on what seems to be working in other communities. Decisions regarding how much of each type of service to deploy or where to deploy specific services are made using intuition and local knowledge. While a community group may agree on what needs to be done, the specifics of quantity, location and implementation model can paralyze a community as they try to interpret disparate data points. As we have demonstrated in the HIV prevention sphere, predictive modeling may provide a quantitative tool to facilitate action.

An implementation strategy for predictive modeling in public health must include effort across three domains: community engagement, data collection, and model building. Based on the experience with the two case studies presented, development of community decision making processes and data collection and sharing are precursors to the use of predictive modeling tools. While a single organization may be able to fulfill all these functions for some community health issues, for most including overdose death reduction, it is generally diffuse even in rural communities. At least a small group of organizations or government departments must coalesce and agree on collective action. The group must include key data holders and organizations who are willing to change their approach based on the outcome of simulation experiments. While knowledge of model driven decision making may not exist in the early stages of community engagement, an investment in using data for decision making is proving to be an essential precursor to willingness to adopt recommendations from modeling experiments. However, the relationship between data trust and predictive model usage is circular. Modeling can increase trust in data as it demonstrates utility of data collection and consolidation.

One critical purpose of predictive modeling of complex systems is for scenario planning to assess the impact of system shocks and to compare the relative advantage of different combinations of interventions and different implementation strategies for interventions. In our examples, we show that first, the levels of increased service that were initially discussed were far below that necessary to achieve stated goals of the community. Second, we demonstrated that some implementation strategies that had strong support had low to no potential impact, e.g., additional naloxone distribution in a saturated market. These simple initial models can bring relief to communities who feel that nothing they do has an impact after collecting data and watching deaths increase year over year. Now, these communities have a better idea of the level of effort required. They understand the need to include multiple strategies and varying methods of implementation. We expect that the next level of questioning in our ongoing community engagement may be not "What happens if we do x?", but "What are the ways we can achieve a x% change in our outcome of interest?".

So far in our case studies, simulation experiments have asked only about potential changes on the intervention side. As the overdose crisis has evolved through several iterations, increased value of using MDDS would be gained when communities also ask "what if" questions on changes on the problem side of the equation. For example, modeling questions about the effect of the cannabis supply becoming contaminated with fentanyl, the impact of a new deadly psychoactive substance, or the impact of a service disruption like a pandemic or extreme weather event might improve planning. As we have moved into a fourth stage of the overdose crisis, one exemplified by contamination of all substances with lethal contaminants, we must begin to consider how strategies must change to be effective. Even recent data describes the past, and communities must develop the skills to imagine future crises in the same way that industry does. Using MDDS can help communities become more agile in their response to change.

Communities can better use data and improve outcomes by combining ABM with quality improvement activities to assess ongoing impact of community strategy and identifying potential targets for improvement as the problem evolves over time.

5. Future research

Additional research is needed to ascertain the efficacy of MDDS as a meta-implementation strategy to improve outcomes for substance use and other community health concerns. Most research to date has assessed various models' ability to predict outcomes, but not the efficacy of modeling as a tool for decision-making to improve community health. Questions that need to be explored are whether predictive models affect decision making at the community level, how or whether collective acceptance of model-based decision making impacts the decisions of individual actors within the collective, and whether modeling improves the sharing and use of data for community health improvement. Are there universal design elements that are required for useful MDDS tools? Thus far, our work has been to design models based on community interest, data availability and questions that are asked. A universal design or template would make MDDS more easily described, disseminated and adopted.

Additionally, further research is necessary to understand the unique implementation issues for MDDS. Our early studies described here have identified some of the standard implementation issues such as staff and leadership turnover and data availability as hindrances to full implementation of MDDS. We are interested in whether there are unique issues that affect any aspect of MDDS. For example, collective decision making as a critical part of the MDDS process is different from organizational change where a single leader is ultimately responsible for decision making. Collective action affects data collection, the design of the predictive model, and the questions asked - all of which may impact implementation of predictive modeling and the process of implementing a strategy to address the community health problem based on model predictions. Barriers and facilitators may be different or interact in different ways than in an organization. The complexity of community -based decision making, involving and impacting multiple organizations, needs further study.

CRediT authorship contribution statement

Lia Chin-Purcell: Project administration, Writing – original draft, Writing – review & editing. **Holly Hills:** Writing – review & editing, Conceptualization, Writing – original draft. **C. Hendricks Brown:** Conceptualization, Funding acquisition, Supervision, Writing – original draft, Writing – review & editing, Methodology. **Marianne J Dean:** Writing – review & editing. **Timothy Burns:** Writing – review & editing. **Kimberly Johnson:** Conceptualization, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Joshua T. Barnett:** Writing – review & editing. **Wouter Vermeer:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

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