



A decision-making model to optimize the impact of community-based health programs

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ABSTRACT

Hospitals and clinics are increasingly interested in building partnerships with community-based organizations to address the social determinants of health. Choosing among community-based health programs can be complex given that programs may have different effectiveness levels and implementation costs. This study develops a decision-making model that can be used to evaluate multiple key factors that would be relevant in resource allocation decisions related to a set of community-based health programs. The decision-making model compares community-based health programs by considering funding limitations, program duration, and participant retention until program completion. Specifically, the model allows decision makers to select the optimal mix of community-based health programs based on the profiles of the population given the above constraints. The model can be used to improve resource allocation in communities, ultimately contributing to the long-term goal of strengthening cross-sector partnerships and the integration of services to improve health outcomes.

1. Introduction

Cardiovascular disease (CVD) and diabetes are prevalent chronic conditions that are not only costly to the health care delivery system but also result in significant disability and death in the United States and around the world (Goeree et al., 2013). Modifiable lifestyle factors such as smoking, diet, and physical activity can impact the prevention and management of these chronic health conditions (Buttar et al., 2005). As such, the adoption of healthy lifestyles and giving individuals and communities greater control over the development of strategies to improve their health are increasingly important to reduce the burden of disease (Fedder et al., 2003).

Although there are many promising community-based health programs that can effectively improve the prevention and management of CVD and diabetes, policymakers face multiple challenges when deciding which community-based health programs should be selected and implemented across different communities. Challenges to implementation include a highly diverse range of programs with varying levels of demonstrated effectiveness, changing community health needs, and limited evidence on the return on investment of the programs. Poor implementation is common and has contributed to the failure of many

community-based health programs (Matheson et al., 2013). Even though the impact of these programs can be improved with better implementation (WHO, 2014), limited evidence exist to guide decisions to accomplish this outcome (Milat et al., 2011; Wolfenden et al., 2016). Compared with implementation studies undertaken in clinical settings, existing research has found few trials in community settings targeting CVD and diabetes (McFadyen et al., 2018; Wolfenden et al., 2017). Existing evidence on the effectiveness of community-based health programs is scarce in terms of examples of successful implementation (McFadyen et al., 2018; Wolfenden et al., 2016; Wolfenden et al., 2017).

The impact of community-based health programs is typically measured by projected costs and benefits, but there is scarce limited guidance and methodological approaches to make projections when many health conditions and services need to be considered. The use of cost-effectiveness ratios (Eichler et al., 2004; Heidenberger, 1996; Zaric et al., 2002) to allocate resources does not allow for considering important factors in the decision-making process such as a highly diverse range of programs with different demonstrated impact in the community (i.e. effectiveness), programs time duration, the funding levels to support community-based health programs, and expected participant retention. Optimization-based resource allocation models

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can be based on a variety of factors and are meant primarily to inform decision makers of the best alternatives under various scenarios.

This study presents a decision-making model for resource allocation and planning that can be used to decide where new investments should be directed to achieve better community health outcomes. The decision-making model allows for the selection of a program or programs to be funded while considering practical constraints, such as funding limitations, program duration, and participant retention. Specifically, the model allows decision makers to select the optimal mix of community-based health programs based on the profiles of the population given the above constraints. The key challenge is to decide which program or set of programs should be funded given a limited budget. The model developed in this study can help decision-makers address multiple key issues simultaneously while it also aligns well with the RE-AIM (Reach Effectiveness Adoption Implementation Maintenance) planning and evaluation framework in that it can be used to inform community-based health program selection and design when there is limited data on effectiveness, sustainability, and implementation (Finlayson et al., 2014; Glasgow and Estabrooks, 2018).

2. Methods

The multi-criteria decision-making model proposed here takes the form of an integer program (IP), constructed to work in conjunction with an existing agent-based model (Li et al., 2014; Li et al., 2018) that is designed to capture individual health progression and study emergent CVD-related population health outcomes (diabetes, myocardial infarction, stroke, and death) over a specified time period. An IP is a mathematical model that is used to search for the best integer solution for a problem given a set of problem limitations or constraints. IP models have been used in resource allocation problems in multiple settings including healthcare, telecommunication networks, and scheduling. In general, IPs have two parts: an objective function and a set of constraints. The objective function guides the resource allocation decisions based on the problem constraints. The objective function selected for this study seeks to obtain the largest overall health benefit for every dollar spent.

Fig. 1 illustrates the framework of the decision-making model. The red dotted line is used to highlight the data and actors (i.e., community, public health decision makers, and prevention programs) involved in the implementation of the decision-making model. The symbols included in Fig. 1 are the parameters used in the decision-making model to represent the data inputs. The outputs from the agent-based model were used as input parameters to the decision-making model that seeks to optimize funding decisions in terms of which community-based health program or programs will have the greatest health impact. Participant simulated outcomes, participant, funding, and program data are included as inputs in the decision-making model. Participant data includes the number of

residents in the community and the number of persons with one or more health conditions. Program data includes targeted health conditions and interventions to modify health behaviors, sample size, intervention length, and total cost per person per year.

2.1. Agent-based model

We used an agent-based model that was developed to capture different behaviors and health conditions over time (Li et al., 2014). The agent-based model allows for the examination of the progression of the health conditions and cardiovascular diseases considered in this study which are diabetes, myocardial infarction (MI), and stroke. In the agent-based model, each agent (person) is defined according to seven behavior and health factors, including smoking, physical activity, healthy diet, healthy weight, cholesterol, blood pressure, and blood glucose, as well as by age, gender, and having a history of MI or stroke. The model can generate a user-specified population, capture the dynamic changes of health behaviors and factors, and report a set of health outcomes and mortality over a time period of interest. A previous study using the model assessed how four “hypothetical” and independent lifestyle interventions (i.e., “quit smoking”, “promote healthy diet”, “improve physical activity”, and “reduce obesity”) would reduce the number of people with diabetes, a history of MI and a history of stroke in 5, 10, 15 and 20 years into the future (Li et al., 2014).

The decision-making model described in the next section is designed to complement the agent-based model or other similar models designed to study disease progression. Results from the agent-based model (i.e., number of people with diabetes, a history of MI and a history of stroke in 5, 10, 15 and 20 years for each intervention) can be used as input to the decision-making model. The impact of each program was estimated as follows. Let α represent the percentage (%) of the population representing the reduced number of people with diabetes after implementing the “promote healthy diet” lifestyle intervention for 5 years. Now, let β represent the percentage (%) of the population representing the reduced number of people with diabetes after implementing the “improve physical activity” lifestyle intervention for 5 years. Then, $\alpha + \beta$ is used to estimate the percentage (%) of the population representing the reduced number of people with diabetes after implementing a community-based health program that implements both lifestyle interventions for 5 years.

The decision-making model discussed in the next subsection recommends which program or programs to fund by measuring and comparing existing community-based health programs while considering environmental constraints, such as funding limitations, population characteristics, and expected participant retention.

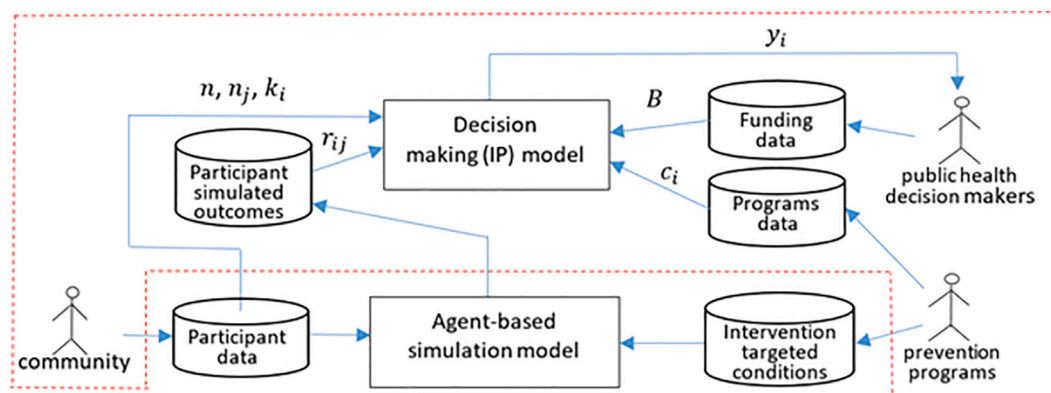


Fig. 1. Research methodology.

2.2. Decision-making model for community-based health programs selection

Let I denote the community-based health programs indexed $i \in I$ and let J denote health conditions indexed $j \in J$. Set J includes diabetes, myocardial infarction (MI), and stroke. Parameter n represents the number of residents in the community and n_j represents the number of persons with health condition j . Parameter B represents the *monetary budget* available to fund community-based health programs every year and parameter c_i represents the yearly cost per person when participating in community-based health program i . Finally, parameter k_i represents the maximum *expected participant retention* and r_{ij} represents the ratio (%) of participants with health condition j that are expected to show improved health outcomes after participating in program i . Parameter r_{ij} is computed using the output of the agent-based model. Using the example provided in the previous section, assume that a community-based health program ($i = 1$) implements both “*promote healthy diet*” and “*improve physical activity*” lifestyle interventions. In addition, assume that $j = 1$ represents diabetes. Then $r_{11} = \alpha + \beta$. Fig. 1 illustrates the data sources from where input parameters for the model are obtained.

The decisions to be made by the model are represented by the following two decision variables. Decision variable y_i is a binary variable that equals one if community-based health program i is selected to be funded by the model and equals zero otherwise. Decision variable x_{ij} represents the number of participants with health condition j participating in program i .

The model can now be stated using the provided definitions for the sets, parameters, and decision variables. The objective function (Eq. (1)), $\max \sum_i \sum_j r_{ij} x_{ij}$ guides the decisions to be made by the model. In this

case, the model maximizes the number of participants with health condition j which are expected to show improved health outcomes after participating in program i . In other words, the model finds the best combination of community-based health programs that will maximize the number of participants who will show improved health outcomes after implementing the recommended programs. The model constraints varied based on the different experimental scenarios studied. Eq. (2), $\sum_i \sum_j x_{ij} \leq n$, limits the number of people that can participate in community-based health programs to the number of people in the studied community. Eq. (3), $\sum_j x_{ij} \leq M y_i, \forall i \in I$, is a selection constraint

which is used to decide which programs maximize the performance goals of the objective function. Eq. (4), $\sum_i x_{ij} \leq n_j, \forall j \in J$, limits the decisions to be made to the total number of residents in the community with health condition j . Eq. (5), $x_{ij} \geq 0$ and integer, $\forall i \in I, \forall j \in J$, limit the decision variables x_{ij} to assume integer positive values. Eq. (6), $y_i \in \{0, 1\}, \forall i \in I$, limits the decision variables y_i to assume binary values.

Eqs. (1) to (6) represent the “base IP model.” The “base IP model” can be used to assess what is the impact of considering different time durations when selecting the community-based health programs. Additional constraints must be added to the “base model” to answer other key questions such as what is the impact of considering the expected participant retention when selecting the community-based health programs, (Eq. (7), $\sum_j x_{ij} \leq k_i, \forall i \in I$, which imposes an upper bound for the expected participant retention until program completion (k_i) to each community-based health program i), and what are the implications of different funding levels when selecting the community-based health programs (Eq. (8), $\sum_i \sum_j c_i x_{ij} \leq B$, which limits the number of programs to be selected to the budget constraint for the year in terms of participant costs).

2.3. Population and community-based health programs data

In this study, a set of parameters define and describe the population where the community-based programs will be considered for adoption and implementation (Li et al., 2014). Nationally representative data was obtained from the Behavioral Risk Factor Surveillance System (BRFSS). The BRFSS is a telephone survey targeting American adults living in households, and the survey includes standard core questions related to preventive health practices and chronic health conditions. We extracted data from the 2012 BRFSS for all American adults between ages 20–79 (CDC, 2019) to identify the population profile needed for input modeling. The population was divided according to their age, race/ethnicity, health behaviors, health conditions, and history of cardiovascular disease. The health conditions and cardiovascular diseases considered were diabetes, myocardial infarction (MI), and stroke. The population age varies from 20 to 79 years where the mean age was 45.5. On average, 51.1% of studied adults were female, 80% were non-smokers, 36.9% were physically active, 24.4% followed a healthy diet, 8.3% had diabetes, 3.7% had a history of MI, and 2.3% had a history of stroke.

Seven community-based health programs were considered to demonstrate how the proposed decision-making model works. The programs considered in this study are (1) Community Outreach and Cardiovascular Health, (2) Liverpool Primary Care Trust Lay Health Trainers, (3) Healthlines Telehealth, (4) Maryland Community Health Worker Outreach, (5) Community-wide Cardiovascular Health Awareness Program (CHAP), (6) University of East Anglia Impaired Fasting Glucose Program (UEA-IFG), and (7) HealthyLiving Partnerships to Prevent Diabetes (HELP PD). Programs were selected based on the availability of published data and their characteristics are discussed in Table 1. These are community-based health programs designed to address diabetes, myocardial infarction (MI), and stroke. They address these health conditions by managing healthcare utilization better, helping people quit smoking, improve physical activity, promote healthy diet, and reduce obesity. Table 1 identifies with an “X” the lifestyle intervention implemented by each community-based improvement program. For example, the 6th community-based improvement program listed in Table 1 implements the “promote healthy diet” and “improve physical activity”. Therefore, $\alpha + \beta$ is used to estimate the expected number of reduced cases of participants (r_{ij}) with health condition j when participating in program i .

2.4. Simulated experiments with case study

The decision-making model was applied to a case study generated from the literature in which seven different community-based health programs (see Table 1) are considered for funding purposes. Multiple scenarios were considered to study the robustness of the decisions evaluated by the model. Three experimental factors (EF) were considered in building the scenarios: 1) *community-based health programs time duration*; 2) *the funding levels to support community-based health programs*; and 3) *expected participant retention*.

The “*community-based health program time duration*” considers the amount of time the program(s) will run before measuring the overall health impact in the community. In this research, three levels for this experimental factor are considered: 5 years, 10 years, and 20 years. These three levels were selected based on intervention lengths reported in the literature (Boelsen-Robinson et al., 2015). It is assumed that a specific program is repeated continually to the same set of participants. The “*funding levels to support community-based health programs*” factor studies whether program decisions are sensitive to the funding levels available to support community-based health programs. Funding sources include foundations, private, and government. In this research, three levels for this experimental factor are considered: \$100,000 per year, \$250,000 per year, and \$500,000 per year.

The “*expected participant retention*” studies the number of participants

Table 1
Community-based health programs.

#	Program name	Quit smoking	Improve physical activity	Promote healthy diet	Reduce obesity	Age mean (years)	# of people that can be potentially served by the program	Intervention length (months)	Total cost per participant per year (\$)	Reference
1	Community outreach and cardiovascular health	X	X	X	X	54	150	12	\$264.00	(Allen et al., 2014)
2	Liverpool primary care trust lay health trainers		X	X		53	150	12	\$477.00	(Barton et al., 2012)
3	Healthlines telehealth	X	X	X	X	67	150	12	\$184.00	(Dixon et al., 2016)
4	Maryland community health worker outreach			X	X	57	50	36	\$ 48.00	(Fedder et al., 2003)
5	Community-wide cardiovascular health awareness (CHAP)	X	X	X	X	75	600	3	\$393.00	(Goeree et al., 2013)
6	University of East Anglia Impaired Fasting Glucose Program (UEA-IFG)		X	X		59	300	6	\$600.00	(Irvine et al., 2011)
7	HealthyLiving partnerships to prevent diabetes (HELP PD)		X	X	X	60	75	24	\$386.00	(Lawlor et al., 2013)

Table 2

Impacts for the implementation of different community-based programs based on 18 scenarios/simulations Descriptive results of community-based health programs (CBHP) selected per combination of following experimental factors: 1) community-based health programs time duration; 2) the funding levels to support community-based health programs; and 3) expected participant retention.

Experimental factors (EF)			Performance measures				
(EF1) CBHP time duration in years	(EF2) \$ funding levels to support CBHP	(EF3) % expected participant retention	CBHP selected using methodology	Total # of participants for selected CBHP	Number of participants with improved health	Percentage of participants with improved health (%/year)	\$ annual cost (\$/per participant enrolled)
5	100,000	85	1,3,4,5	427	35	8.30 (1.66)	99,862.49 (233.87)
		100	1,3,4	508	45	8.85 (1.77)	99,913.44 (196.68)
	250,000	85	1,3,4,5	809	74	9.20 (1.84)	249,989.10 (309.01)
		100	1,3,4,5	895	82	9.20 (1.84)	249,812.40 (279.12)
	500,000	85	1,2,3,4,5,6,7	1331	90	6.80 (1.36)	499,617.50 (375.37)
		100	1,3,4,5,7	1533	97	6.35 (1.27)	499,788.70 (326.02)
10	100,000	85	1,3,4,5	427	73	17.20 (3.44)	99,862.49 (233.87)
		100	1,3,4	508	90	17.70 (3.54)	99,913.44 (196.68)
	250,000	85	1,3,4,5	806	160	19.80 (3.96)	249,013.70 (308.95)
		100	1,3,4,5	895	178	19.90 (3.98)	249,812.40 (279.12)
	500,000	85	1,2,3,4,5,6,7	1331	196	14.75 (2.95)	499,497.70 (375.28)
		100	1,3,4,5,7	1533	200	13.10 (2.62)	499,788.70 (326.02)
20	100,000	85	1,3,4,5	427	117	27.35 (5.47)	99,841.14 (233.82)
		100	1,3,4	508	140	27.65 (5.53)	99,913.44 (196.68)
	250,000	85	1,3,4,5	809	238	29.45 (5.89)	249,964.80 (308.98)
		100	1,3,4,5	895	265	29.55 (5.91)	249,785.60 (279.09)
	500,000	85	1,2,3,4,5,6,7	1331	279	20.95 (4.19)	499,497.70 (375.28)
		100	1,3,4,5,7	1533	288	18.80 (3.76)	499,788.70 (326.02)

Note: Community-based health programs (CBHP) described in detail in Table 1. The 7 CBHPs are defined as: (1) Community Outreach and Cardiovascular Health, (2) Liverpool Primary Care Trust Lay Health Trainers, (3) Healthlines Telehealth, (4) Maryland Community Health Worker Outreach, (5) Community-wide Cardiovascular Health Awareness Program (CHAP), (6) University of East Anglia Impaired Fasting Glucose Program (UEA-IFG), and (7) HealthyLiving Partnerships to Prevent Diabetes (HELP PD).

that are expected to be enrolled in their program until completion or retention rate. In this research, two levels for this experimental factor are considered: 85% and 100%. These levels were selected based on retention rates of successful programs reported in the literature (Carroll et al., 2011). A 100% level implies that all the people who entered the program completed the program. 85% retention means that 15% of the participants who started the program did not complete all the required activities. A total of 18 experimental combinations were considered to understand their impact on three performance measurements: 1) community-based health programs selected; 2) % of participants with improved health; and 3) annual cost per participant enrolled in the selected community-based health programs.

3. Results

Table 2 summarizes the computational results for the experimental design discussed previously in methods. Table 2 shows the results for an example of a community with 10,000 residents and which parameters are reported in (Li et al., 2014). A total of 18 experiments were conducted considering different levels for the experimental factors (EF): 1) community-based health programs time duration; 2) the funding levels to support community-based health programs; and 3) expected participant retention. For each combination of experimental factors, Table 2 reports the community-based health programs selected for the example of a community, the total number of participants for the selected programs, the percentage of participants with improved health, and the annual cost per participant enrolled.

The community-based health programs selection was significantly related to the funding levels to support community-based health programs and the expected participant retention. As observed in Table 2, the community-based health programs selected did not change when those two experimental factors remain the same and only the community-based health programs time duration varies. However, the results also show that the % of participants with improved health increases as the time duration of the implemented community-based health programs increases. Therefore, it is evident that the longer the time duration for the program the better the results in terms of participants with improved health.

Fig. 2 displays the % of participants with improved health conditions when evaluating only the time durations at different levels (i.e., 5 years, 10 years, and 20 years). As stated earlier, the plot shows that keeping the

programs running for a longer period of time provides more benefits to the community. The 20-year time duration (i.e., gray bars) shows higher benefits in terms of the % of participants with improved health conditions when considering all possible combinations of the experimental factors. The maximum % of participants with improved health conditions occurs when community programs 1, 3, 4, and 5 are selected to be implemented for a time duration of 20 years.

In terms of funding levels, the results show that at a \$250 K funding level the best results are observed with about 6% of participants showing improved health outcomes when programs are implemented for 20 years. An interesting result is observed when funding is increased to \$500 K. Fig. 2 shows that the percentage of participants with improved health decreases by about 2% when compared to a level of funding of \$250 K. The reasoning behind this result is that at the \$500 k funding level more community programs can be implemented. However, those additional programs might not be appropriate for the needs of the community and might end up not producing the expected results. Limiting the funding to \$250 K forces the model to select programs that will have a larger impact on the community participants which will improve their health outcomes.

Fig. 2 also depicts the impact of considering the participants' retention rate when selecting the community-based health programs to be implemented in the community. Fig. 2 shows that the impact of the retention rate factor, in terms of the % of participants with improved health, is correlated to the funding level factor. Consider the first four groups of bars depicted in Fig. 2 where the funding available is fixed to \$100 K (first two groups) and \$250 k (groups three and four). The results show that on average about 0.02% percentage increase or about 4 additional participants will show improved health outcomes when the retention rate of 100% is compared against 85%. This result does not hold when funding level considered is \$500 k. Consider the last two groups of bars depicted in Fig. 2. The results for funding level \$500 k show a decrease in the % of participants with improved health per year when the retention rate factor is 100%. The reasoning behind this result is that at the \$500 k funding level more community programs can be implemented. However, those additional programs might not be appropriate for the needs of the community and might end up not producing the expected results. A retention rate of 85% will have less participants in programs that are not as effective which will increase the % of participants with improved health. Therefore, the results show that more funding to support more community-based health programs does

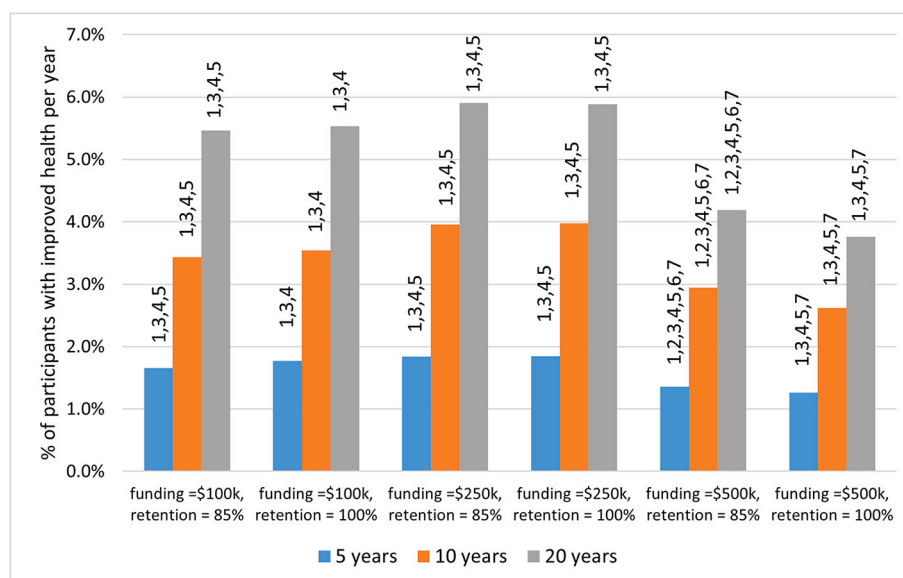


Fig. 2. Proportion of participants with improved health conditions when considering different time durations for programs implementation [program selection displayed at the top of each bar]. Note: Community-Based Health Programs (CBHP) described in detail in Table 1.

not necessarily translate into better health outcomes for the community.

4. Discussion

This study discusses how community-based health programs that seek to address cardiovascular disease (CVD) and diabetes can be compared using a decision-making model that considers funding limitations, population characteristics, and participant retention until program completion. The model can be useful to decision-makers who need to consider multiple key issues simultaneously while it also aligns well with the RE-AIM (Reach Effectiveness Adoption Implementation Maintenance) planning and evaluation framework in that it can inform community-based health program selection and design when there is limited data on effectiveness, sustainability, and implementation (Glasgow and Estabrooks, 2018). Our approach can be used to strengthen cross-sector partnerships and facilitate the integration of services and systems to improve health outcomes. Program selection decisions were associated with modest improvements in terms of the percentage of program participants with improved health.

Previous studies of community-based health programs have reported that programs are influential in changing the behavior of participants (Driscoll et al., 2008; Lv et al., 2014). In addition, several studies have reported that most community-based health programs do not produce significant changes in health outcomes for a ten year period (Brand et al., 2014; Kloeck et al., 2006; Merzel and D'Afflitti, 2003; Wolfenden et al., 2014). Our study shows that significant changes in health outcomes are possible if the selected community-based health programs are kept running for about 20 years. The simulation-based results show that implementing the appropriate community-based health programs for a 20-year period could provide a 48% increase in the percentage of participants with improved health per year when compared to a 10-year period. Our approach of program selection has several strengths. First, the underlying ABM is the first model that can capture changes of important lifestyle factors (e.g., smoking, diet, and physical activity) simultaneously as well as their impact on CVD risk factors and outcomes. Second, the underlying ABM is flexible for capturing population heterogeneity because it includes a large set of important risk factors for CVD and allows for automatic generation of simulated individuals (i.e., agents) based on the demographic and health profiles of the studied population users define. Finally, the decision-making model complements the agent-based model by providing optimized selection of programs without using a traditional trial-and-error approach.

Funding availability and structures are sometimes key barriers to action. The model and framework presented in this paper can resolve funding limitation barriers by allocating the limited funds to programs that will provide the best benefit to the community. One of the strengths of our study is the use of data from different sources. The data analysis combined with the proposed decision-making framework elicited information considering a broad range of barriers such as limited funding. The results showed that high funding availability does not necessarily translate to better outcomes to the community. For instance, having sufficient funding might push decision makers to implement programs that are not effective for the community which would produce counterproductive results. For instance, for a specific community only some of the available programs might help participants improved health outcomes. However, if spending the overall funding available is required then the decisions will include additional programs that might end up not producing the expected results. Our results showed that limiting the funding to \$250 K forced the decision-making framework to only select programs that will produce meaningful benefits to community participants by shifting the focus to health outcomes.

5. Conclusions

Improving community-level health outcomes is difficult, and it takes time to observe positive changes on health outcomes. As observed in the

results, the level and intensity of community-based programs required to observe improved health outcomes in a community depends on multiple factors. Making the most appropriate decisions, in terms of which programs to implement, is challenging. In addition, those decisions must consider that sometimes more than a decade of program implementation and evaluation might be needed to produce significant improvement outcomes. The decision-making framework presented in this paper considers these factors and provides a route of action for a specific community.

Unlike previous research, we modeled the decision-making process of selecting and funding of community-based health programs considering program duration, funding limitations, and participant retention. We found that different combinations of these factors are important when the goal is to achieve the highest expected number of participants with improved health outcomes in a community. The modeling approach presented here provides a feasible, cost-effective way to understand and evaluate different scenarios to inform policy decisions.

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Declaration of competing interest

None disclosed.

References

- (CDC), C.f.D.C.a.P, 2019. Behavioral Risk Factor Surveillance System: BRFSS 2012. https://www.cdc.gov/brfss/annual_data/annual_2007.htm.
- Allen, J.K., Himmelfarb, C.R.D., Szanton, S.L., Frick, K.D., 2014. Cost-effectiveness of nurse practitioner/community health worker care to reduce cardiovascular health disparities. *J. Cardiovasc. Nurs.* 29, 308.
- Barton, G.R., Goodall, M., Bower, P., Woolf, S., Capewell, S., Gabbay, M.B., 2012. Increasing heart-health lifestyles in deprived communities: economic evaluation of lay health trainers. *J. Eval. Clin. Pract.* 18, 835–840.
- Boelsen-Robinson, T., Peeters, A., Beauchamp, A., Chung, A., Gearon, E., Backholer, K., 2015. A systematic review of the effectiveness of whole-of-community interventions by socioeconomic position. *Obes. Rev.* 16, 806–816.
- Brand, T., Pischke, C.R., Steenbock, B., Schoenbach, J., Poettgen, S., Samkange-Zeeb, F., Zeeb, H., 2014. What works in community-based interventions promoting physical activity and healthy eating? A review of reviews. *Int. J. Environ. Res. Public Health* 11, 5866–5888.
- Buttar, H.S., Li, T., Ravi, N., 2005. Prevention of cardiovascular diseases: role of exercise, dietary interventions, obesity and smoking cessation. *Exp. Clin. Cardiol.* 10, 229.
- Carroll, J.K., Yancey, A.K., Spring, B., Figueroa-Moseley, C., Mohr, D.C., Mustian, K.M., Sprod, L.K., Purnell, J.Q., Fiscella, K., 2011. What are successful recruitment and retention strategies for underserved populations? Examining physical activity interventions in primary care and community settings. *Transl. Behav. Med.* 1, 234–251.
- Dixon, P., Hollinghurst, S., Ara, R., Edwards, L., Foster, A., Salisbury, C., 2016. Cost-effectiveness modelling of telehealth for patients with raised cardiovascular disease risk: evidence from a cohort simulation conducted alongside the Healthlines randomised controlled trial. *BMJ Open* 6, e012355.
- Driscoll, D.L., Rupert, D.J., Golin, C.E., McCormack, L.A., Sheridan, S.L., Welch, B.M., Poehlman, J.A., 2008. Promoting prostate-specific antigen informed decision-making: evaluating two community-level interventions. *Am. J. Prev. Med.* 35, 87–94.
- Eichler, H.G., Kong, S.X., Gerth, W.C., Mavros, P., Jönsson, B., 2004. Use of cost-effectiveness analysis in health-care resource allocation decision-making: how are cost-effectiveness thresholds expected to emerge? *Value Health* 7, 518–528.
- Fedder, D.O., Chang, R.J., Curry, S., Nichols, G., 2003. The effectiveness of a community health worker outreach program on healthcare utilization of West Baltimore city Medicaid patients with diabetes with or without hypertension. *Ethn. Dis.* 13, 22–27.
- Finlayson, M., Cattaneo, D., Cameron, M., Coote, S., Matsuda, P.N., Peterson, E., Sosnoff, J.J., 2014. Applying the RE-AIM framework to inform the development of a multiple sclerosis falls-prevention intervention. *Int. J. MS Care* 16, 192–197.
- Glasgow, R.E., Estabrooks, P.E., 2018. Peer reviewed: pragmatic applications of RE-AIM for health care initiatives in community and clinical settings. *Prev. Chronic Dis.* 15.
- Goeree, R., von Keyserlingk, C., Burke, N., He, J., Kaczorowski, J., Chambers, L., Dolovich, L., Paterson, J.M., Zagorski, B., 2013. Economic appraisal of a community-wide cardiovascular health awareness program. *Value Health* 16, 39–45.

- Heidenberger, K., 1996. Dynamic project selection and funding under risk: a decision tree based MILP approach. *Eur. J. Oper. Res.* 95, 284–298.
- Irvine, L., Barton, G.R., Gasper, A.V., Murray, N., Clark, A., Scarpello, T., Sampson, M., 2011. Cost-effectiveness of a lifestyle intervention in preventing type 2 diabetes. *Int. J. Technol. Assess. Health Care* 27, 275–282.
- Kloek, G.C., van Lenthe, F.J., van Nierop, P.W., Koelen, M.A., Mackenbach, J.P., 2006. Impact evaluation of a Dutch community intervention to improve health-related behaviour in deprived neighbourhoods. *Health Place* 12, 665–677.
- Lawlor, M.S., Blackwell, C.S., Isom, S.P., Katula, J.A., Vitolins, M.Z., Morgan, T.M., Goff Jr., D.C., 2013. Cost of a group translation of the diabetes prevention program: healthy living partnerships to prevent diabetes. *Am. J. Prev. Med.* 44 (S381–S389).
- Li, Y., Kong, N., Lawley, M., Pagán, J.A., 2014. Assessing lifestyle interventions to improve cardiovascular health using an agent-based model. In: *Proceedings of the Winter Simulation Conference 2014*. IEEE, pp. 1221–1232.
- Li, Y., Kong, N., Lawley, M.A., Pagán, J.A., 2018. An agent-based model for ideal cardiovascular health, decision analytics optimization in disease prevention treatment. *Wiley* 241–255.
- Lv, J., Liu, Q.-M., Ren, Y.-J., He, P.-P., Wang, S.-F., Gao, F., Li, L.-M., 2014. A community-based multilevel intervention for smoking, physical activity and diet: short-term findings from the community interventions for health programme in Hangzhou, China. *J. Epidemiol. Community Health* 68, 333–339.
- Matheson, G.O., Klügl, M., Engebretsen, L., Bendiksen, F., Blair, S.N., Björjesson, M., Budgett, R., Derman, W., Erdener, U., et al., 2013. Prevention and management of non-communicable disease: the IOC consensus statement, Lausanne 2013. *Sports Med.* 43, 1075–1088.
- McFadyen, T., Chai, L.K., Wyse, R., Kingsland, M., Yoong, S.L., Clinton-McHarg, T., Bauman, A., Wiggers, J., Rissel, C., et al., 2018. Strategies to improve the implementation of policies, practices or programmes in sporting organisations targeting poor diet, physical inactivity, obesity, risky alcohol use or tobacco use: a systematic review. *BMJ Open* 8, e019151.
- Merzel, C., D’Afflitti, J., 2003. Reconsidering community-based health promotion: promise, performance, and potential. *Am. J. Public Health* 93, 557–574.
- Milat, A.J., Bauman, A.E., Redman, S., Curac, N., 2011. Public health research outputs from efficacy to dissemination: a bibliometric analysis. *BMC Public Health* 11, 1–9.
- WHO, 2014. Global Status Report on Noncommunicable Diseases 2014. World Health Organization.
- Wolfenden, L., Wyse, R., Nichols, M., Allender, S., Millar, L., McElduff, P., 2014. A systematic review and meta-analysis of whole of community interventions to prevent excessive population weight gain. *Prev. Med.* 62, 193–200.
- Wolfenden, L., Milat, A.J., Lecathelinais, C., Skelton, E., Clinton-McHarg, T., Williams, C., Wiggers, J., Chai, L.K., Yoong, S.L., 2016. A bibliographic review of public health dissemination and implementation research output and citation rates. *Prev. Med. Rep.* 4, 441–443.
- Wolfenden, L., Nathan, N.K., Sutherland, R., Yoong, S.L., Hodder, R.K., Wyse, R.J., Delaney, T., Grady, A., Fielding, A., et al., 2017. Strategies for Enhancing the Implementation of School-Based Policies or Practices Targeting Risk Factors for Chronic Disease (Cochrane database of systematic reviews).
- Zaric, G.S., Brandeau, M.L., Biology, 2002. Dynamic resource allocation for epidemic control in multiple populations. *Math. Med.* 19, 235–255.