Minimizing HIV Infections in Ohio through Optimal Resource Allocation: A Linear/Integer Programming Approach

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Introduction

Despite nearly four decades of relentless advocacy, groundbreaking research, and the committed delivery of comprehensive services aimed at diagnosing, preventing, and treating HIV, the United States stands at a pivotal juncture with the tangible possibility of ending the HIV epidemic. Since its identification in 1981, HIV has profoundly impacted millions of lives nationwide. Currently, thanks to the persistent efforts of stakeholders across various sectors and significant advances in biomedical and scientific research, there exist robust HIV diagnostics, prevention methods, and enhanced care and treatment models. Moreover, innovative laboratory and epidemiological techniques now allow for precise identification of HIV's most rapid transmission vectors, enabling targeted interventions to halt the virus's spread effectively.

The development of the HIV National Strategic Plan (HIV Plan) embodies a collaborative effort, drawing on insights and feedback from an array of fields including public health, healthcare, research, among others, with a vision for the United States to become a place where new HIV infections are rare, everyone is aware of their HIV status, and all individuals with HIV receive high-quality care and treatment devoid of stigma and discrimination.

However, distributing resources to state and major metropolitans in the US for efficient ways of curbing the HIV infections remain a critical challenge, particularly in regions like Ohio, where disparities in access to healthcare and prevention services persist.

Firstly, the dynamic nature of the HIV epidemic, with varying rates of transmission across different populations and regions, necessitates a flexible and targeted approach to resource distribution. Secondly, limited funding and competing health priorities require strategic decision-making to ensure that investments yield the highest possible impact on HIV prevention. Furthermore, disparities in access to healthcare and prevention services, influenced by socio-economic, racial, and geographical factors, complicate efforts to reach the most at-risk populations effectively. Lastly, the evolving landscape of HIV prevention, including new technologies and approaches, demands ongoing evaluation and adaptation of strategies to incorporate the most effective interventions. The upcoming discussion will explore how these tools and knowledge can be strategically applied to optimize resource allocation in Ohio, aiming to minimize HIV infections efficiently.

Problem Statement

Despite considerable advancements in HIV diagnosis, prevention, and treatment, Ohio continues to face significant challenges in curbing the spread of HIV among its population. The state's ability to effectively manage and allocate resources to combat HIV is crucial, yet complex, given the varying rates of infection across different regions and communities. The primary challenge lies in optimizing the deployment of limited resources such as funding, medical personnel, and preventive technologies to areas and populations where they are most needed and can be most effective.

The goal of this research is to develop a mathematical model using linear and integer programming techniques to optimize the allocation of HIV prevention and treatment resources in Ohio. This model aims to minimize new HIV infections by identifying and targeting at-risk individuals within the state. By integrating data on current infection rates, transmission patterns, demographic factors, resource availability, equity, and cost-effectiveness, the model will provide a strategic framework for decision-makers. This framework will help prioritize interventions, allocate resources efficiently, and achieve the greatest possible reduction in HIV transmission rates.

Objective of Study

This study aims to

1. create a basic linear/integer programming model for optimizing HIV resource allocation Ohio.
2. develop the basic model to a more complex one incorporating demographic, equity, and cost-effectiveness constraints.
3. identify and prioritize high-risk areas and demographics within Ohio.
4. equip health policymakers and key stakeholders with a sophisticated, data-driven decision-support tool to achieving the goals outlined in the HIV National Strategic Plan.

Background of Study

In the United States, the Centers for Disease Control and Prevention (CDC) allocate funds to state and major metropolitan area health departments, known as "grantees," for HIV prevention interventions. These grantees also distribute additional HIV prevention funds from state governments, private donations, and interest groups for prevention activities.

The process of acquiring and distributing funds involves two key decision points for the grantees: developing requests for proposals (RFPs) and allocating funds based on submitted proposals. Before creating RFPs, members of the local HIV prevention community, part of Community Planning Groups (CPGs), identify high-priority populations for targeted prevention efforts in the upcoming year. Priority populations, such as men who have sex with men (MSM) and intravenous drug users (IDUs), are the focus of HIV prevention efforts due to their high rates of HIV infection and risky behavior. Most grantees have multiple CPGs to address the diverse needs of different geographic regions, each with its own list of priority populations.

Once priority populations are identified, grantees develop a comprehensive HIV prevention plan submitted to the CDC to request funding. After securing funds, grantees issue RFPs for conducting prevention activities, inviting responses from community-based organizations (CBOs) or local health departments. Before releasing RFPs, grantees determine the combinations of priority populations and geographic regions for which prevention proposals will be solicited. They may also recommend preferred prevention activities based on funding priorities for CPG-identified priority populations, equity considerations across geographic regions, and factors of cost-effectiveness.

Following the submission of intervention proposals in response to RFPs, jurisdictions decide how to allocate funds to proposal applicants. This allocation process represents the second major decision point for grantees, who must decide where and to whom (i.e., implementers of prevention activities) funds should be distributed to maximize the prevention of potential infections.

In this study, the CDC aimed to develop mathematical tools to guide the allocation of prevention resources based on principles of cost-effectiveness. Focusing on the initial stage of the allocation process, the project aimed to assist grantees in determining the distribution of funds to priority populations/regions to inform the RFP process.

Methodology

The developed Linear Programming (LP) model calculates an allocation that maximizes the weighted count of potential infections prevented, considering the constraints of funding availability, caps on disbursements to individuals at risk, and equity considerations.

Model

Sets

i geographical region where $i=1$ to m

j priority population where $j=1$ to n

Parameters

C	amount of available funding (from CDC and other sources) to be allocated.
c_{ij}	average per-person annual cost to implement one intervention in priority population j in region i
w_{ij}	the weight associated with priority population *j* in region *i* that quantifies CPG priority.
p	maximum percent of difference between max and min funds allocated.
d_{ij}	100% or the maximum percent of available funding to be allocated to priority population *j* in region *i* that is less than 100%
N_{ij}	number of individuals in priority population *j* in region *i*.

e_{ij} total annual number of expected potential infections averted (i.e., the number of infections that would occur in the absence of any investments) per person in priority population *j* in region *i.*

b_{ij} minimum percent of priority population *j* in region *i* to be allocated funding.

k_{ij} minimum percent of available funding to be allocated to priority population j in region *i.*

m_i * minimum percent of available funding to be allocated to region *i.*

a_i * maximum percent of available funding to be allocated to region *i.*

z_{ij} * maximum percent of available funding to be allocated to priority population j in region *i.*

Decision Variables

x_{ij} Funding to allocate to priority population j (as defined by a risk behavior) in geographic region *i*; *i=1* to *m, j=1* to *n*

y_{ij} number of at-risk individuals in priority population *j* and region *i* receiving funds.

Variable

x_max (maximum amount allocated)

x_min (minimum amount allocated)

Objective Function

$$Maximize \sum_{1=m}^{m} \sum_{j=1}^{n} w_{ij} e_{ij} y_{ij}$$

(maximizes the weighted number of potential infections averted)

Subject to

(1) $\sum_{1=m}^{m} \sum_{j=1}^{n} x_{ij} \leq C$ *(budget constraint)*

(2) $y_{ij} \leq d_{ij} N_{ij} \quad \forall i, j$ *(no more than one package of interventions can be funded per individual)*

(3) $c_{ij} y_{ij} = x_{ij} \quad \forall i, j$ *(number of people receiving funds in each priority population j of region i)*

(4) $x_{ij} \geq 0 \quad \forall i, j$ *(non-negativity constraints)*

(5) $y_{ij} \geq 0 \quad \forall i, j$

Equity Constraints

(6) $y_{ij} \geq b_{ij}N_{ij} \quad \forall i, j$ *(Funds allocated to ensure interventions reach a minimum specified percentage of each priority population across all geographic regions.)*

(7) $x_{ij} \geq k_{ij}C \quad \forall i, j$ *(Allocates at least a pre-specified percent of available funds to each priority population j in each geographic region i)*

(8) *Next three constraints asserts that the difference between max and Min funds allocated should within a specified percent of funds available*

$$x\_min \leq x_{ij}$$

$$x_{ij} \leq x\_max$$

$$x\_max - x\_\text{min} \leq p * C$$

(9) $\sum_{j=1}^{n} x_{ij} \geq m_i C \quad \forall i$ *** *(Allocates at least a pre-specified percentage of available funds to each geographic region i)*

(10) $\sum_{j=1}^{n} x_{ij} \geq a_i C \quad \forall i$ *** *(Allocates no more than a pre-specified percentage of available funds to each geographic region i)*

(11) $x_{ij} \leq z_{ij}C \quad \forall i, j$ *** *(Allocates no more than a pre-specified percent of available funds to each priority population j in each geographic region i)*

The objective function of this LP maximizes the weighted number of potential infections averted. The potential number of infections that may be averted is the expected number of HIV infections that could occur given current risk behaviors. This number is derived using Pinkerton and Abramson's Bernoulli model for HIV transmission [9], considering both sexual behaviors and risks associated with injection drug use.

The objective function incorporates the priority weights determined by the CPG(s). These weights reflect the relative importance of each priority population as determined by the CPG(s). The constraints on the LP include: a budget constraint (1); the restriction that no more than one intervention or one package of interventions can be funded per individual (2); number of people receiving funds in each priority population matching the funds allocated (3); and non-negativity constraints (4)(5).

In the proposed model, a suite of equity constraints is available, offering users the discretion to select those pertinent to their objectives. This research will concentrate on a specific equity constraint, namely, ensuring that the distribution of funds guarantees a minimum threshold of intervention coverage for each priority population across all geographic areas (Constraint 6).

We shall also consider the constraint that each priority population receive a pre-specified minimum amount of the total available funds (Constraint 7).
Additionally, we will scrutinize the constraint mandating that the disparity between the maximum and minimum funds allocated remains within a predetermined percentage of the total funds (Constraint 8). This targeted approach allows for a detailed examination of the allocation process's fairness and its adherence to equitable distribution principles.

Constraints 9, 10, 11 and 12 (optional), aim to maintain equitable distribution of funds within each region and/or priority population, emphasizing the importance of fair resource allocation across different geographic locations and specific demographic groups.

Data Processing

The model was created using data acquired through the analysis of the 2023 report titled "HIV/AIDS Integrated Epidemiologic Profile for Ohio," which was produced by the Department of Health in Ohio.
The HIV transmission modalities were classified into five distinct categories in the report. These categories include Male-to-male sexual contact (MSM), Heterogeneous sexual contact (HSC), Injection Drugs Users (IDU), both Male-to-male sexual contact and Injection Drugs Users (MSM/IDU), and an unknown group.
Male-to-male sexual contact (MSM) refers to sexual interactions between men, including those identifying as gay. Transgender women are included in the male-to-male sexual contact. transmission category if assigned male at birth and risk factor history indicates sex with males. Please note this is for the categorization of HIV transmission categories only and not to describe sexual orientation.
Heterogeneous sexual (HSC) contact refers to sexual interactions between individuals of different sexes, typically involving a man and a woman.
Injection drug users (IDU) refer to individuals who administer drugs intravenously, using needles to inject substances directly into their bloodstream.
The group designated as Male-to-Male Sexual Contact and Injection Drug Users (MSM/IDU) encompasses individuals who engage in both male-to-male sexual activities and intravenous drug use.
The term "unknown group" refers to instances of new infections where the mode of transmission has not been determined. This categorization is essential in health surveillance to identify cases where the exact pathways of infection spread are unclear.

The number of people in each priority population (N_{ij}) was obtained as follows.

Number of MSM in each region = Number of people in region × percentage of males in each region × percent of new infections transmitted through male-to-male sexual contact

Number of IDU in each region = Number of people in region × percent of new infections transmitted through drug injections

Number of MSM/IDU in each region = Number of people in region × percent of new infections transmitted through male-to-male sexual contact and drug injections

Number of HSC in each region = Number of people in the region × percent of new infections transmitted through heterogenous sexual contact.

Number of people in unknown group in each region = Number of people in the region × percent of new infections identified as unknown.

The weight(w_{ij}) for each priority population was obtained as follows.
The priority population identified in the region is ranked based on the number of new infections recorded. For instance, in region 1, Male-to-male sexual contact (64%) was the leading mode of transmission reported among all persons diagnosed with an HIV infection. Injection drug use (IDU) accounted for 2%, male-to-male sexual contact/IDU accounted for 7%, heterosexual contact accounted for 17%, and the transmission category was unknown for 10% of persons diagnosed with HIV infection. In this case Male-to-male sexual contact was ranked 5, heterosexual contact ranked as 4, unknown ranked as 3, male-to-male sexual contact/IDU ranked 2 and Injection drug use ranked as 1.

$$\boldsymbol{w_{ij}} = \frac{\boldsymbol{rank\ of\ the\ prioity\ population}}{\boldsymbol{total\ number\ of\ priority\ populations\ identified\ in\ the\ region}}$$

Expected number of new HIV infections given the current risk behaviors was calculated as follows.

$$\boldsymbol{e_{ij} = number\ of\ new\ infections\ in\ the\ priority\ population\ \times\ 10}$$

This formula was formulated to make it simple to test the model. The actual procedure used in calculating e_{ij} is through the Pinkerton and Abramson models.

The cost per person per annum of implementing an intervention was chosen as the average of the ranges given Ryan White HIV/AID 2022 Data Report.

The parameters d_{ij},C , p, k_{ij} were randomly chosen. In our analysis, we shall consider various choices of these parameter and how they affect the results.

The map of Ohio; indicating the demarcation into 11 regions for the purpose of health resource allocation.

data;

set geographical_region:= Region1 Region2 Region3 Region4 Region5 Region6 Region7 Region8 Region9 Region10 Region11;

set priority_population:= MSM IDU MSMIDU HSC Unknown;

MSM = Men sex Men , IDU = Intravenous Drug Users

param fund_available:= 50000000;

param percent_diff_max_min:= 0.09;

param expected_infections:

	MSM	IDU	MSMIDU	HSC	Unknown:=
Region1	231	8	29	71	42
Region2	57	2	8	20	12
Region3	920	20	80	282	565
Region4	364	34	42	161	187
Region5	95	0	19	70	70
Region6	36	0	9	9	61
Region7	37	39	9	49	20
Region8	465	405	96	501	212
Region9	414	58	49	116	190
Region10	15	0	0	15	40
Region11	747	189	84	506	358;

param weight:

	MSM	IDU	MSMIDU	HSC	Unknown:=
Region1	1	0.2	0.4	0.8	0.6
Region2	1	0.2	0.4	0.8	0.6
Region3	1	0.2	0.4	0.6	0.8
Region4	1	0.2	0.4	0.6	0.8
Region5	1	0	0.25	0.5	0.5
Region6	0.6	0	0.2	0.2	1
Region7	1	0.6	0.2	0.8	0.4
Region8	1	0.8	0.2	0.4	0.6
Region9	1	0.4	0.2	0.6	0.8
Region10	0.33	0	0	0.33	1
Region11	1	0.4	0.2	0.8	0.6;

param cost_per_person:

	MSM	IDU	MSMIDU	HSC	Unknown:=
Region1	35000	10000	43000	35000	43000
Region2	35000	10000	43000	35000	43000
Region3	39000	11000	45000	39000	43000
Region4	35000	10000	43000	35000	43000
Region5	35000	0	43000	35000	43000
Region6	35000	0	43000	35000	43000
Region7	35000	10000	43000	35000	43000
Region8	39000	11000	45000	39000	43000
Region9	35000	10000	43000	35000	43000
Region10	35000	0	0	35000	43000

Region11	39000	11000	45000	39000	43000;

param max_percent_fund_to_ij:

	MSM	IDU	MSMIDU	HSC	Unknown:=
Region1	0.9	0.9	0.9	0.9	0.9
Region2	0.9	0.9	0.9	0.9	0.9
Region3	0.9	0.9	0.9	0.9	0.9
Region4	0.9	0.9	0.9	0.9	0.9
Region5	0.9	0	0.9	0.9	0.9
Region6	0.9	0	0.9	0.9	0.9
Region7	0.9	0.9	0.9	0.9	0.9
Region8	0.9	0.9	0.9	0.9	0.9
Region9	0.9	0.9	0.9	0.9	0.9
Region10	0.9	0	0	0.9	0.9
Region11	0.9	0.9	0.9	0.9	0.9;

param number_of_persons_in_priority_pop:

	MSM	IDU	MSMIDU	HSC	Unknown:=
Region1	252551	16106	56373	136906	80533
Region2	178331	11145	39010	47369	55728
Region3	564327	21729	86919	155152	608439
Region4	307232	49176	61471	119130	270472
Region5	162215	0	53892	98160	192472

Region6	67768	0	32857	16428	209466
Region7	72830	82673	19684	51178	43304
Region8	300144	432381	54047	288254	414365
Region9	255195	20832	62496	145825	239570
Region10	76504	0	0	153008	204011
Region11	480115	187871	83498	500990	354868;

param min_percent_fund_to_ij:

Regions	MSM	IDU	MSMIDU	HSC	Unknown:=
Region1	0.01	0.01	0.01	0.01	0.01
Region2	0.01	0.01	0.01	0.01	0.01
Region3	0.01	0.01	0.01	0.01	0.01
Region4	0.01	0.01	0.01	0.01	0.01
Region5	0.01	0	0.01	0.01	0.01
Region6	0.01	0	0.01	0.01	0.01
Region7	0.01	0.01	0.01	0.01	0.01
Region8	0.01	0.01	0.01	0.01	0.01
Region9	0.01	0.01	0.01	0.01	0.01
Region10	0.01	0	0	0.01	0.01
Region11	0.01	0.01	0.01	0.01	0.01;

ANALYSIS

We first set C=50million USD, p = 0.09 and $d_{ij} = 0.9$, $k_{ij} = 0.01$ for all priority populations in each region. This outcome is produced.

```
people_funded [*,*]

: HSC IDU MSM MSMIDU Unknown:=

Region1 15 50 15 12 12

Region10 15 0 15 0 12

Region11 13 46 115 12 12

Region2 15 50 15 12 12

Region3 13 46 115 12 100

Region4 15 50 15 12 12

Region5 15 0 15 12 12

Region6 15 0 15 12 12

Region7 15 50 15 12 12

Region8 13 409 115 12 12

Region9 15 50 127 12 12

;


funds [*,*]

: HSC IDU MSM MSMIDU Unknown :=
```

Region1	525000	5e+05	525000	516000	516000
Region10	525000	0	525000	0	516000
Region11	507000	506000	4485000	540000	516000
Region2	525000	5e+05	525000	516000	516000
Region3	507000	506000	4485000	540000	4300000
Region4	525000	5e+05	525000	516000	516000
Region5	525000	0	525000	516000	516000
Region6	525000	0	525000	516000	516000
Region7	525000	5e+05	525000	516000	516000
Region8	507000	4499000	4485000	540000	516000
Region9	525000	5e+05	4445000	516000	516000

;

Regions 3, 8, and 11 contains the three major cities Cleveland, Cincinnati, and Columbus respectively. In these regions, male-to-male sexual contact group were ranked with highest priority with a $4.4M allocation each. In region 9, male-to-male sexual contact group received a $4.4M allocation with 127 people funded.

In this model, we make the simplifying assumption that funds spent will avert the number of potential infections as estimated by the Bernoulli process equations when in reality spending the funds and providing an intervention does not guarantee aversion of an infection.

We shall consider two different selections of d_{ij},C , p, k_{ij} and its result is summarized in the following table.

Regions	Number of potential infections averted	Amount allocated	Number of potential infections averted	Amount allocated
Case 1: $d_{ij} = 0.9$, C = \$50million , p = 0.01, $k_{ij} = 0.01$			**Case 2**: $d_{ij} = 0.9$, C = \$10million, p = 0.01, $k_{ij} = 0.01$	
1	104	2582000	22	568000
2	104	2564000	22	568000
3	286	10338000	42	1517000
4	104	2582000	22	568000
5	54	2082000	12	468000
6	54	2082000	12	468000
7	104	2582000	22	568000
8	561	10547000	113	2169000
9	216	6502000	44	1338000
10	42	1566000	9	339000
11	198	6554000	43	1427000
Total	**1827**	**49981000**	**383**	**9998000**

For a constant d_{ij}, p, k_{ij} across all priority populations within each region, there is an equal percentage of amount being allocated to region 1, region 2, and region 7. Regions 5 and 6 received same amounts of funds. The regions with the three major cities (Columbus, Cincinnati, Cleveland) received relatively higher amount of funds.
Overall, for a \$50million and \$10million funds allocated, there will be 1827 and 383 potential infections averted, corresponding to 22.51% and 4.72% of the expected infections, respectively. This implies, the greater the amount of resource to be allocated, the higher the number of potential infections averted.

Conclusion

The model developed in the report considers a multitude of factors, including funding availability, intervention costs, demographic data, and expected infection rates. By maximizing the weighted count of potential infections prevented, the model aims to achieve the dual objectives of reducing HIV transmission and ensuring equitable access to prevention and treatment services across different geographic regions and priority populations.
A key highlight of the study is the emphasis on targeted interventions tailored to high-risk areas and demographics within Ohio. By identifying and prioritizing these specific groups, the model equips health policymakers and stakeholders with a data-driven decision-support tool aligned with the goals of the HIV National Strategic Plan. This approach underscores the importance of precision and efficiency in resource allocation to achieve maximum impact in curbing the spread of HIV.
Moreover, the study recognizes the dynamic nature of the HIV epidemic and the need for continuous evaluation and adaptation of prevention strategies. By integrating data on infection rates, transmission patterns, and cost-effectiveness considerations, the model provides a comprehensive framework for optimizing the allocation of resources and minimizing new HIV infections in Ohio.
In conclusion, this study offers a robust and innovative approach to addressing the challenges of HIV prevention and treatment in Ohio. Through its mathematical modeling and data-driven strategies, the study

provides a roadmap for decision-makers to make informed choices, prioritize interventions effectively, and work towards reducing HIV transmission rates in the state.

Future Work

- Extend the analysis to evaluate the long-term impact of different intervention strategies on reducing HIV transmission rates and improving health outcomes to provide valuable insights into the sustainability of the interventions over time. Projecting trends over several years can help in understanding the long-term effectiveness of resource allocation strategies.

- Consider the incorporation of behavioral factors and social determinants of health into the model would offer a more comprehensive understanding of the complex dynamics influencing HIV transmission. By studying the impact of factors such as stigma, discrimination, and access to healthcare services, the model can better inform prevention efforts and intervention strategies.

- Conduct a cost-effectiveness analysis to compare the efficiency of different intervention strategies in averting infections per unit cost would aid in identifying the most cost-effective approaches for HIV prevention and treatment. Engaging with stakeholders, including policymakers, healthcare providers, and community organizations, is crucial to ensure the relevance and applicability of the analysis findings. Collaboration can facilitate the translation of research insights into actionable strategies for combating HIV effectively.

References

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Brandeau ML (2004) Allocating resources to control infectious diseases. In: Brandeau ML, Sainfort F, Pierskalla WP (eds) Operations research and health care: a handbook of methods and applications. Kluwer, Boston, MA

https://odh.ohio.gov/know-our-programs/hiv-aids-surveillance-program/Data-and-Statistics
The Ohio department of health website provides reports on HIV/AIDS infections.

https://ryanwhite.hrsa.gov/sites/default/files/ryanwhite/data/rwhap-annual-client-level-data-report-2022.pdf
Provides an idea the cost of intervention and how interventions are implemented.

Pinkerton SD, Abramson PR (1998) The Bernoulli-process model of HIV transmission: applications and implications. In: Holtgrave DR (ed) Handbook of economic evaluation of HIV prevention programs. Plenum, New York

Appendix

Explanation of Key terms

1. **HIV**: Human Immunodeficiency Virus, the virus that causes AIDS by attacking the body's immune system.
2. **AIDS**: Acquired immunodeficiency syndrome.
3. **Ohio**: A state in the Midwestern of United States.
4. **Resource allocation**: The process of distributing resources such as funding, personnel, and technologies to achieve specific goals effectively.
5. **Linear programming:** A mathematical method used to optimize resource allocation by maximizing or minimizing a linear objective function subject to linear constraints.
6. **Integer programming:** A mathematical optimization technique where decision variables are restricted to integer values, often used in resource allocation models with discrete choices.
7. **Prevention:** Strategies and interventions aimed at reducing the risk of HIV transmission and infection.
8. **Treatment:** Medical care and interventions provided to individuals living with HIV to manage the virus and its effects on the body.
9. **Healthcare disparities:** Differences in access to healthcare services and outcomes based on factors such as race, income, and geographic location.
10. **Demographic factors:** Characteristics of populations such as age, gender, race, and ethnicity that can impact HIV transmission and healthcare access.
11. **Cost-effectiveness:** Evaluating the efficiency of interventions by comparing the costs incurred with the outcomes achieved in preventing HIV infections.
12. **Stakeholder engagement**: Involving individuals and organizations with a vested interest in HIV prevention and treatment in decision-making processes and implementation strategies.
13. **Intervention strategies:** Approaches and actions implemented to prevent HIV transmission, promote testing, and improve health outcomes among at-risk populations.
14. **Epidemiology:** The study of disease patterns, causes, and effects within populations, including the spread and impact of HIV infections.

Ohio HIV Prevention Planning Regions

Region 1	Region 5	Region 9
Defiance	Carroll	Clark
Fulton	Coshocton	Darke
Henry	Harrison	Greene
Lucas	Holmes	Miami
Ottawa	Jefferson	Montgomery
Sandusky	Stark	Preble
Williams	Tuscarawas	
Wood	Wayne	
Region 2	**Region 6**	**Region 10**
Ashland	Athens	Champaign
Crawford	Belmont	Hancock
Erie	Guernsey	Hardin
Huron	Meigs	Logan
Knox	Monroe	Mercer

Marion
Richland
Seneca
Wyandot

Morgan
Muskingum
Noble
Perry
Washington

Paulding
Putnam
Shelby
Van Wert

Region 3/Ryan White Part A-Cleveland
Ashtabula
Cuyahoga
Geauga
Lake
Lorain
Medina

Region 4
Columbiana
Mahoning
Portage
Summit
Trumbull

Region 7
Adams
Fayette
Gallia
Hocking
Jackson
Lawrence
Pike
Ross
Scioto
Vinton

Region 8
Brown
Butler
Clermont
Clinton
Hamilton
Highland
Warren

Region 11/Ryan White Part A-Columbus
Delaware
Fairfield
Franklin
Licking
Madison
Morrow
Pickaway
Union

AMPL MODEL;

```
set geographical_region;

set priority_population;

set pre_specified{geographical_region, priority_population};

param fund_available; ## total budget in form of money (in USD)

param percent_diff_max_min; #percentage difference between max and min funds
allocated
```

```
param expected_infections{geographical_region, priority_population};

###total annual number of expected potential infections averted

## (i.e., the number of infections that would occur in the absence of any investments)

## per person in priority population j in region i.

param weight{geographical_region, priority_population};

## the weight associated with priority population j in region i that quantifies CPG priority.

param cost_per_person{geographical_region, priority_population};

#average per-person annual cost to implement one intervention in priority population j in
region i

param max_percent_fund_to_ij{geographical_region, priority_population};

#100% or the maximum percent of available funding to be allocated to priority
population j in region i that is less than 100%

param number_of_persons_in_priority_pop{geographical_region, priority_population};

## number persons in each priority population j in region i.

param min_percent_fund_to_ij{geographical_region, priority_population};

### minimum percent of available funding to be allocated to priority population j in
region i

var funds{geographical_region, priority_population} >=0;
```

```
#Funding to allocate to priority population j (as defined by a risk behavior) in geographic region

var people_funded{geographical_region, priority_population} >=0 integer;

# number of individuals receiving funds in priority population j in region i

var funds_max >= 0;

var funds_min >= 0;

maximize number_averted: sum{i in geographical_region, j in priority_population} (weight[i,j] * expected_infections[i,j] * people_funded[i,j]); # (funds[i,j] / cost_per_person[i, j]));

#maximizes the number of potential infections averted

subject to budget_constraint: sum{i in geographical_region, j in priority_population} funds[i, j] <= fund_available;

##budget constraint

#subject to one_intervention_per_person{i in geographical_region, j in priority_population}: funds[i,j] / cost_per_person[i,j] <= max_percent_fund_to_ij[i,j] * number_of_persons_in_priority_pop[i,j] ;

subject to one_intervention_per_person{i in geographical_region, j in priority_population}: people_funded[i,j] <= max_percent_fund_to_ij[i,j] * number_of_persons_in_priority_pop[i,j] ;

## no more than one package of interventions can be funded per individual
```

```
subject to min_fund_to_ij{i in geographical_region, j in priority_population}: funds[i,j] >=
min_percent_fund_to_ij[i,j] * fund_available;

### at least a pre-specified percent of available should allocated to priority pop j in
region i

subject to number_receiving_funds{i in geographical_region, j in priority_population}:
cost_per_person[i,j] * people_funded[i,j] = funds[i,j];

###NEXT THREE CONSTRAINTS ARE TO ENSURE THE DIFFERENCE BETWEEN
LARGEST AND SMALLEST FUNDS ALLOCATED TO BE LESS THAN A CERTAIN
PERCENTAGE OF THE BUDGET.

subject to min_funds{i in geographical_region, j in priority_population}: funds_min <=
funds[i,j];

subject to max_funds{i in geographical_region, j in priority_population}: funds[i,j] <=
funds_max;

subject to difference_in_funds{i in geographical_region, j in priority_population}:
funds_max - funds_min <= percent_diff_max_min * fund_available ;
```