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| RESEARCH ARTICLE

Optimizing Vaccine Distribution Networks in Heterogeneous Populations Using Geospatial Data and Demographic Risk Models

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| ABSTRACT

Effective and equitable vaccine distribution is a complex logistical challenge, especially during pandemics. Traditional, one-size-fits-all strategies often fail to address the heterogeneity within populations, leading to inadequate service for high-risk and vulnerable subgroups. This study introduces a novel, integrated approach to optimize vaccine distribution networks by leveraging multi-source geospatial data and advanced demographic risk models. Methods: The proposed framework utilizes Geographic Information Systems (GIS), spatial statistics, and operational research to overcome the limitations of standard models. It dynamically integrates key metrics—including population density, vulnerability, healthcare access, and logistical constraints—to effectively prioritize resource allocation. This integration allows for a nuanced, data-driven approach that moves beyond simplistic population-based strategies. Results: The optimized distribution strategy allocates resources based not only on density but also on vulnerability and access metrics, ensuring that the most at-risk communities are prioritized. This refined approach enables the effective deployment of mobile vaccination centers and strategic placement of fixed sites. By considering epidemiological risk and socio-economic determinants, this framework significantly enhances accessibility and equity, preventing the exacerbation of existing health disparities. Conclusion: The integration of geospatial and demographic risk modeling provides a more nuanced and equitable framework for vaccine resource allocation, thereby enhancing public health outcomes during mass vaccination efforts. Further refinement through microplanning is essential, particularly in resource-limited settings, to precisely identify and reach all target populations.

| KEYWORDS

Vaccine Distribution Optimization, Geospatial Health Analytics, Health Equity, Facility Location-Allocation Modeling, Demographic Risk Stratification

| ARTICLE INFORMATION

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1. Introduction

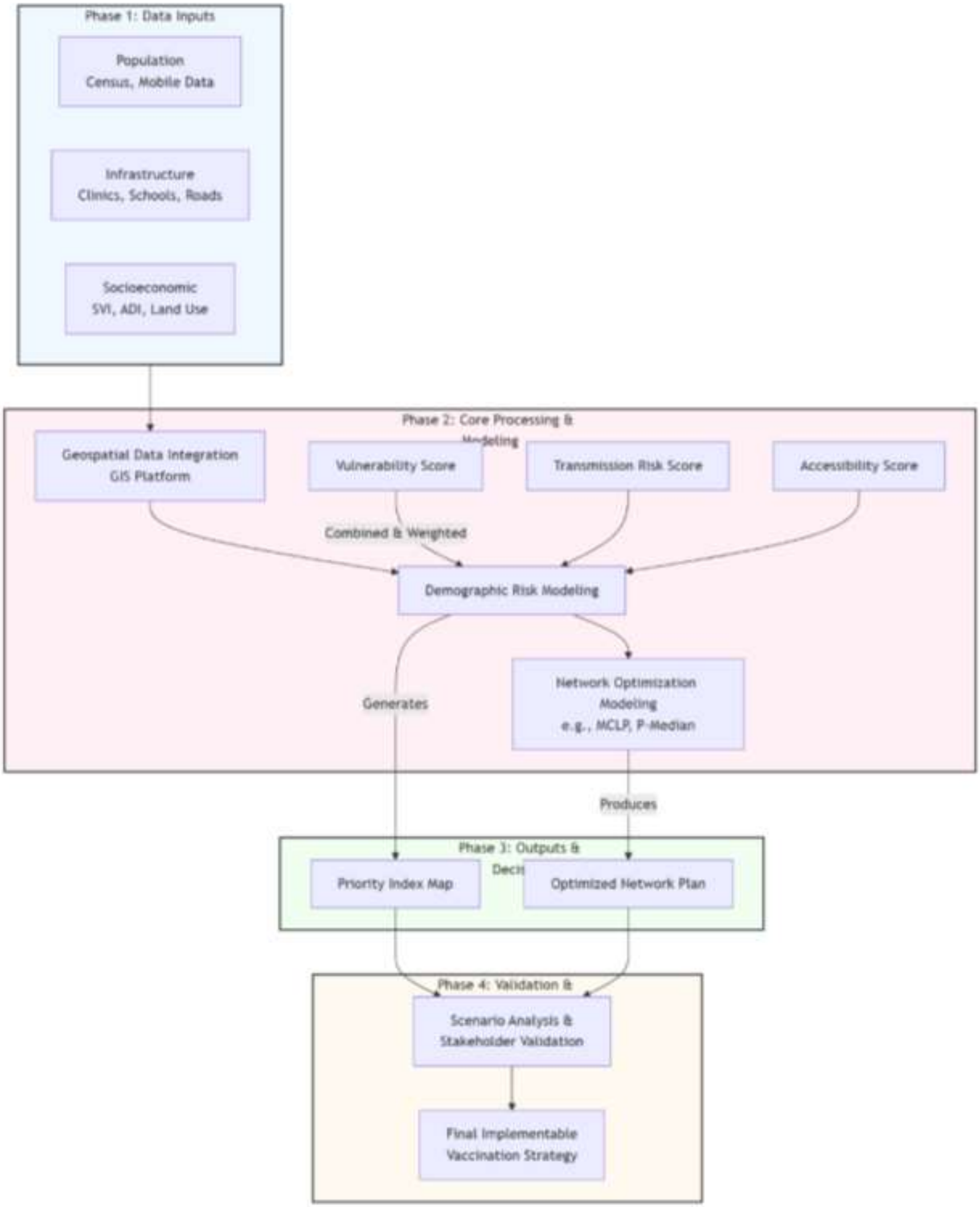

Diagram1: A flow diagram illustrating the three core components and their inputs/outputs.

The COVID-19 pandemic has been a shining example of how current vaccine distribution plans are incredibly suboptimal. Advances in medical research and development have been highly successful at producing vaccines at an impressive speed, however, lack in certain areas that have now been grossly exposed by the distribution process (Bubar et al., 2021). A key aspect of that was the heterogeneity of the population being distributed to. Differences in rates of susceptibility and transmission, as well as potential medical and other types of care, are not the same across every community. Therefore, a "best fit" distribution method in a homogenous population is inefficient and unfair when applied to the real world, heterogeneous population.

The rapidly developing tools of geospatial technology and data analytics, coupled with the time-tested tools of operations research is an area where the research in this field has an incredible opportunity to make an impact. The central thesis of this work is that by thoughtfully combining data on location, such as healthcare facility location, transportation infrastructure and other components with relevant population risk factors (age, pre-existing conditions, socioeconomic status, etc.) then we can construct a more efficient and equitable vaccine distribution network.

2. Core Components of the Integrated Framework

2.1. Geospatial Data Integration

The backbone of the first framework is high-resolution, multi-layered geospatial data.

● Population: The denominator of the population for planning is the primary layer. The base geospatial data for the population is provided by census tracts, but these may not be specific enough to distinguish differences in population at different times (day vs. night) or during travel (Oliver et al., 2020). These additional population shifts, such as by analyzing anonymized mobile phone data, may be helpful for understanding commuting patterns in identifying potential pop-up clinic sites. Reliable and granular data for where the population of interest resides is also a key step in the design of a micro plan: a site-specific plan with highly accurate population estimates and location data (Chaney et al., 2021) (Rocha et al., 2021). This is of particular importance in low resource settings, where geospatial data are often scarce or unreliable. Existing micro plans, which may not be to scale and lack important layers such as distance or barriers to travel, can be expanded upon using new digital mapping methods to more completely and accurately map unreachable settlements.

● Infrastructure: Highly accurate and specific locations of all known hospitals, clinics, pharmacies, and potential mass vaccination sites, such as stadiums or schools. As noted above, the transportation network is also highly relevant and can be modeled as a layer to understand the time required to travel to sites as a key access barrier. Geographic information systems can create and interact with all of these layers to effectively model the population of interest and what is available within the operational environment. Micro plans that provide accurate estimates of population size and location can be used where available, which can address shortfalls in established targets for health coverage (Rocha et al., 2021).

● Environmental and Socioeconomic: Satellite and land-use imagery can help identify hard-to-reach or underserved locations. In addition, information about the Area Deprivation Index (ADI) or CDC's Social Vulnerability Index (SVI) at the community level provides insight into community resilience spatially (Kind & Buckingham, 2018). In sum, many of the datasets are geospatial or can be made into geospatial information. They can be used to create a digital twin of the operational environment and identify highly specific target populations and logistical constraints. It also creates detailed and high-resolution spatial intelligence for use in the next step of this framework, a refined approach to vaccine allocation.

2.2. Demographic Risk Modeling

Mapping age alone limits the resolution to geography, so it is important to calculate an overall risk score for the sub-populations.

● Vulnerability Score: What is the risk of bad outcomes? This can be measured with age structure, comorbidities (diabetes, heart conditions) and congregate living (nursing homes, jails). On the other hand, a community's resilience or adaptive capacity to any of the aforementioned factors can also be considered by including socioeconomic factors like income, education, and proximity to or access to critical services. As such, the most vulnerable members of a population to the disease and who are least able to adapt to the impact of the disease can be identified. (Saidu et al., 2023)

● Transmission Risk Score: What is the risk of being infected? This can be calculated based on housing density, types of essential work, and community mobility patterns. For example, using overall risk models would include other types of epidemiological historical data and real-time surveillance to understand potential emerging outbreak hot spots and proactively identify priority areas before an outbreak for vaccine allocations rather than a reactive response. In addition, when integrated with real-time geospatially referenced data sets these models can also be set up to make dynamic adjustments to the distribution plans when changes to potential risks areas can be identified and vaccine resources redirected to respond to the most emergent needs in the state. (Greenough & Nelson, 2019)

Table 1: A table summarizing the factors and potential data sources for each score

Score Component	Description	Key Factors	Example Data Sources
Vulnerability Score	Risk of severe outcomes if infected.	Age, comorbidities (diabetes, heart disease), congregate living (nursing homes).	Census data, health records, facility registries.
Transmission Risk Score	Risk of being infected and spreading the virus.	Housing density, essential worker density, community mobility patterns.	Mobile phone data, employment statistics, land-use data.
Accessibility Score	Barriers to accessing vaccination services.	Travel time to nearest site, vehicle ownership, digital literacy for online registration.	Transportation networks, census data on vehicle ownership, survey data.
Priority Index	Composite weighted score	Weighted sum of Vulnerability, Transmission, and Accessibility scores.	Output from the combined model.

● Accessibility Score: How easy is it to access a vaccine? This can be based on the actual time needed to travel to the closest location, if they have a personal vehicle and the access to or understanding of technology for registration in an online portal for vaccine appointment scheduling. This would allow for a multi-faceted scoring of neighborhood and community sub-populations that could be used to allocate vaccines to the most high-risk communities. (Rader et al., 2022) This method would also provide a more spatially specific analysis that can move beyond traditional age-based vaccine prioritization to account for different risk levels for each city. (Hong et al., 2022)

Then a final Priority Index can be calculated from weighting and summarizing the scores and mapping to have a granular map-based prioritization of neighborhoods to target for vaccines and site placements.

2.3. Network Optimization Modeling

Facility location-allocation modeling takes the information from the first two steps as input data, in the form of geospatial mapping and risk assessment, to solve an operational research model. With these, the number of sites, their locations, and capacity size can be optimized to achieve a network that provides the maximum coverage at the lowest cost. Popular methods for vaccination site selection are as follows:

● P-Median Models: These are distribution center location-allocation models that seek to minimize the overall travel time of the population to the nearest vaccination site. This is typically done by choosing facility locations such that the sum of demand-weighted travel distances between demand points (population centers) and their closest assigned facility is minimized. - Set Covering Models:

● In contrast, set covering models, as their name implies, instead try to cover all demand points at a set maximum travel distance, with the objective of minimizing the overall number of vaccination facilities needed to provide this coverage (Chen et al., 2022).

Table 2: Table comparing the objectives, strengths, and weaknesses of each model.

Model Type	Primary Objective	Key Strengths	Key Weaknesses / Considerations
P-Median	Minimize total travel distance/time	Maximizes overall system	May neglect remote or low-

	for the population.	efficiency and convenience.	density, high-risk areas.
Set Covering	Cover all demand points within a max distance with the fewest facilities.	Guarantees a baseline level of access for everyone.	Can be resource-intensive; may require many facilities in sparse regions.
Maximal Covering Location Problem (MCLP)	Cover the maximum number of people (weighted by priority) within a distance, with a limited number of facilities.	Ideal for this framework. Directly incorporates the Priority Index to maximize impact.	Requires defining the number of facilities in advance.
Multi-Objective Optimization	Simultaneously optimize multiple goals (e.g., equity, cost, coverage).	Most realistic; can balance competing priorities.	Computationally complex; can be difficult to implement rapidly.

● Maximal covering location problem (MCLP): This is a location-allocation model that selects sites that cover the most number of people (weighted by the Priority Index) within a specified travel time or distance, given that the number of facilities is limited (ReVelle & Church, 1974). An extension of this model can be done to include mobile vaccination clinics, which are optimized to reach the largest number of people in underserved and hard-to-reach areas that may be more spatially fragmented (Goodson et al., 2022). As with location-allocation models, this type of modeling can also account for resource constraints like available vaccine supply, cold-chain capacity, and human resources to produce a set of feasible and efficient clinic deployment strategies (Díaz-Quijano et al., 2023).

● Multi-objective optimization: More advanced models may seek to simultaneously optimize for multiple (and potentially competing) objectives, such as maximizing equity of access to vaccination sites for high-risk subpopulations, minimizing overall logistical costs, and minimizing vaccine wastage (Goodson et al., 2022). These models can be further refined using real-time information on vaccine supply chains and demand surges, thus allowing for adaptive deployment strategies in the event of unforeseen disruptions. On the other hand, the greater the number of decision variables and constraints, the more computationally intensive these sophisticated optimization models will be. As such, they may have limited real-world applicability and usefulness for rapid deployment during public health emergencies. Instead, simpler heuristic approaches or approximation algorithms are often preferred and used, along with sensitivity analyses to understand the trade-offs between model fidelity and operational efficiency. Ultimately, the optimization model chosen for a project will need to be carefully calibrated to the specific circumstances of the public health intervention at hand, to ensure that it is not only analytically rigorous but also practically implementable (Li et al., 2023). This modeling can find ideal vaccination site locations by using preexisting public facilities, such as public schools and hospitals, as initial candidate sites (Cabanilla et al., 2022).

3. Methodology

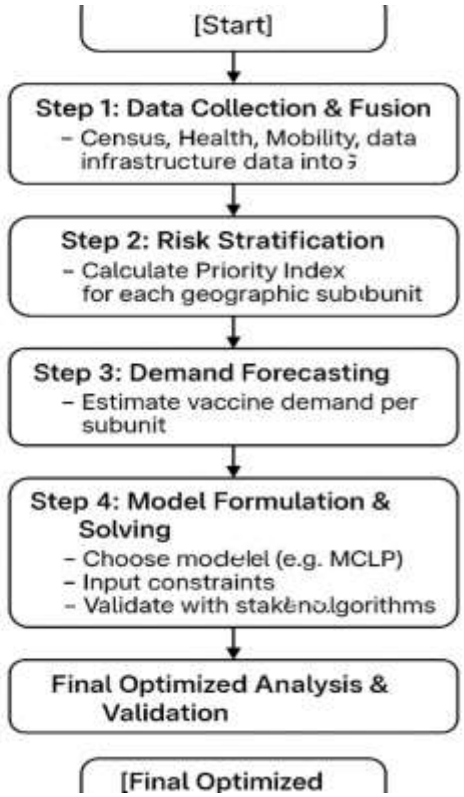

Diagram 2: A detailed flowchart

Step 1. Data Collection & Fusion: Integrate census data, health records, mobility patterns, and infrastructure maps into a comprehensive GIS platform. This includes population demographics, current healthcare facilities, and real-time vaccine availability and uptake rates (Rader et al., 2022). This rich data fusion provides a contextual backdrop for understanding population vulnerabilities and logistical challenges, essential for informed decision-making in vaccine distribution strategies (Shayegh et al., 2023).

Step 2. Risk Stratification: Calculate the Priority Index composite score for each geographic subunit (e.g., census block groups). This index is a weighted combination of epidemiological risk factors (disease prevalence/incidence) and socioeconomic vulnerabilities (poverty, healthcare access) to form a comprehensive measure of community susceptibility and potential for severe outcomes. This stratification allows for a granular and targeted approach to resource allocation, ensuring that areas with the highest need are prioritized appropriately (Shayegh et al., 2023).

Step 3. Demand Forecasting: Estimate the demand for vaccines for each subunit based on its population and Priority Index. The forecast should incorporate variable vaccine hesitancy and acceptance rates across different demographic segments, derived from community-specific surveys and historical health data (Lee et al., 2021). This step is critical for anticipating logistical needs and aligning supply with demand at a granular, local level.

Step 4. Model Formulation & Solving: Choose an appropriate optimization model (MCLP, for instance), enter the constraints (number of sites, budget, cold storage capacities), and run the algorithms to produce candidate networks. This stage can include an integer programming formulation that considers both single and multiple vaccine types and their distribution across a multi-tier cold chain network (Sripada et al., 2023). Additionally, these mathematical models can be expanded to incorporate elements like vaccine wastage, storage capacities, and transportation constraints for increased realism and practical applicability (Ekşioğlu et al., 2023).

Step 5. Scenario Analysis & Validation: Stress-test the optimized networks under various scenarios (supply shortages, new virus strains) and validate the model's efficacy against real-world outcomes or through agent-based simulation. This process is vital for evaluating the robustness of the optimized solutions against uncertainties such as fluctuating vaccine supply or unforeseen demand surges. This is achieved by presenting results to policy and decision-makers using the Traffic Light Analysis Tool to determine how key indicators for a target year change for each scenario when compared to a baseline scenario to reach consensus on optimized models and associated implementation roadmaps (Prosser et al., 2021).

This may include using a comprehensive systems design approach to carry out stakeholder engagement and modeling scenario identifications, which is then followed by in-depth data collection and analysis through document review and interviews of key informants to help optimize the supply chain performance. The evidence-based models generated from the process will require validation in a workshop setting with stakeholders and decision-makers to inform the decisions needed to determine the optimal design of the immunization supply chains. In essence, an iterative process of stakeholder engagement, model refinement, and validation is necessary to ensure the final design is theoretically sound, practically implementable, and aligned with national health priorities (Prosser et al., 2021).

4. Results

One of the major takeaways, however, is that while this data science approach seems to have some promise, it comes with many roadblocks. The first is data privacy. This method is obviously not usable with deidentified data, so the necessary sensitivity of medical and location information of the population must be safeguarded. Model limitations are also to be considered: while the spatial model is dependent on availability and quality of relevant data, it can have its own downstream dependencies, which will not only mirror the availability of data at hand but could also act as a blueprint for perpetuating preexisting biases in the underlying data. Models and algorithms should not be blindly trusted to the exclusion of community engagement and local public health expertise; certain decisions, such as in choosing spatial aggregation techniques to use, must be made with a focus on cultural competency and trust-building.

Additionally, results of the model must be reported clearly and concisely to stakeholders; agreement and buy-in to the scenarios being modeled, after all, is essential for uptake and implementation. The final limitation is one that may seem, at first, to be false. Modeling itself is not an inherently powerful tool for making the "what's best" decision – that decision lies in the hands of stakeholder interpretation, with context from the actual country situation at hand. Quantitative evidence may be of major use in making complex trade-offs, but common sense and a solid understanding of the ground situation in the country under analysis should be used as a starting point for system design analysis (Prosser et al., 2021). An efficient and effective health supply chain (HSC) is one of the vital aspects to achieve public health targets since it enables an uninterrupted supply of the needed equipment (Krautmann et al., 2020).

In contrast, a poorly functioning immunization supply chain was found to be the cause of the inability to provide universal access and high immunization coverage rates; these supply chains are often outdated and inefficient, which leads to disruptions and stock-outs, wastages, and poor quality of vaccines. The immunization system has to be redesigned to be more resilient and responsive in addressing these persistent issues, especially in heterogeneous populations with disparities in health status and outcomes. As such, with its power in geospatial data integration and overlaying it with other factors, such as the demographic risk score model, it is a viable and systematic method for the decision-support problem of developing adaptive strategies for this entrenched issue in immunization and vaccine optimization in vaccine distribution in reaching vulnerable populations (Prosser et al., 2021).

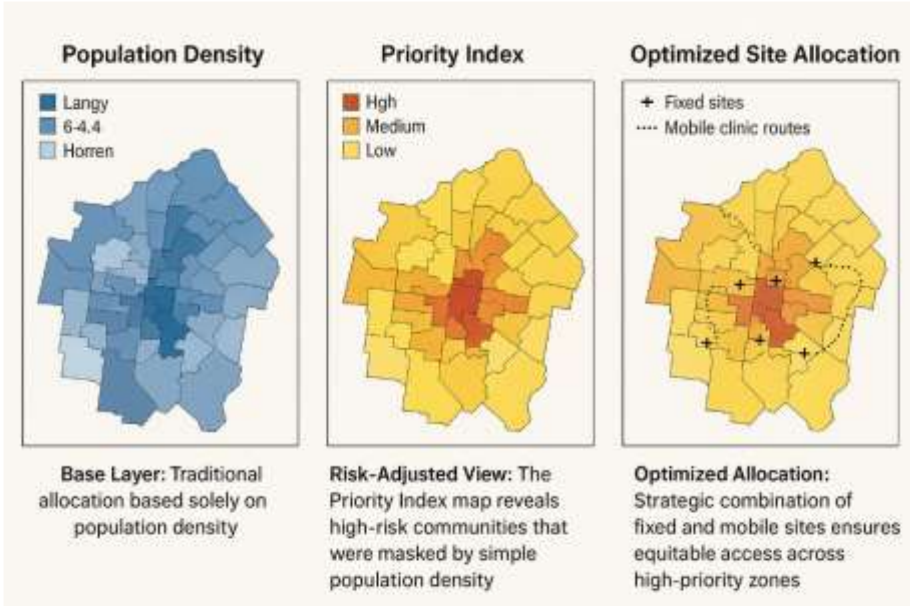

Diagram 3: A sequence of three small maps side-by-side.

Furthermore, these types of operations research analytics and optimization applications are theoretically well-suited for the problem at hand, but practical considerations of current capacity, political and decision-making reality, and likely logistical and throughput impacts may limit the applicability and impact of analytics models developed within the country. A systematic approach to this problem will allow for more strategic use of scarce resources, so the vaccine distribution system is both more efficient and equitable. This will in turn reduce the overall system cost, improve dose delivery rates and increase throughput volume across all facilities in the cold chain as shown by the analysis and cost of various supply chain scenarios.

Optimizing various parts of the vaccine supply chain also helps to improve the resilience of the cold chain so it can better and faster respond to both public health emergencies and routine needs. The quality of the decisions is not solely dependent on cost or computational optimality, and often more decision criteria are at play. These considerations include equity and other qualitative values, which are often difficult to integrate into mathematical programs.

Decision-support frameworks can consider multiple optimizations, like minimizing inventory, ordering, and transportation costs, as well as associated factors such as workforce and personnel expenditures, potential shortages, and other complex real-world constraints across multiple layers of a vaccine cold chain network. For example, linear programming formulations have been used for vaccine allocation to maximize the number of fully immunized children, but these often have assumptions of at least a sufficient vaccine supply and do not account as much for transportation and/or potential staffing capacity. These models, however, are still often simplified for practical purposes, but do not always fully reflect the complexities of real vaccine supply chains with the multiple layers in the supply chain with uncertainties in vaccine production yields and/or fluctuating demand (Sripada et al., 2023).

To handle some of these complexities, a robust optimization method has been developed and shows promise in reducing the cost while maintaining a level of effectiveness, even in the face of high uncertainty in its model parameters. This includes an advanced preprocessing step that can be automatically triggered when a maximum runtime is exceeded by the model. These robust frameworks can optimize many different aspects, like the set of cold chain facilities being ordered from and what vaccines, the quantity ordered, as well as vehicle, inventory, and staffing requirements across multiple tiers in the network. In these more comprehensive models, a mixed-integer linear programming formulation is often used to help represent the underlying relationships and dependencies of a multi-tier cold chain network, with facility transportation and storage costs often being differentiated between fixed and variable costs, along with decisions such as staffing at the vaccination sites.

These robust optimization models have been shown to outperform their deterministic counterparts at varying levels of uncertainty in its modeled parameters, and acts as a more general, reliable tool for use by public health authorities to support their planning and capacity management in a multi-tier cold chain network. The end-to-end, integrated system of decision support allows for optimization of facility set and ordering decisions, vaccine products and allocation quantities, transportation logistics, and capacity, as well as the cold chain link inventory and staffing levels throughout the entire vaccine cold chain.

Additionally, these frameworks explicitly model vaccination personnel availability and their corresponding capacity to deliver doses, directly tying capacity planning for the supply chain to available staffing levels. This includes the development of a robust counterpart to account for uncertainty in the model, further enhancing the reliability of the network design, especially in the context of a vaccine supply chain (Sadjadi et al., 2019). This accounts for uncertainty in key parameters, such as ordering costs, holding costs, and others such as demand, and even potential manufacturing capacity, and in turn is shown to be a more conservative but more effective solution compared to the deterministic version (Sripada et al., 2023).

5. Conclusion

The optimization of vaccine distribution networks is no longer a problem that can be solved with logistics alone. It's a socio-technical one. Imagine a system that combines geospatial intelligence and nuanced demographic risk profiling with mathematical optimization. This would shift vaccine distribution from reactive and undifferentiated to proactive and precision public health. The result? A resilient and equitable public health framework for future crises, with limited vaccines going where they can have the most impact on reducing severe illness and transmission. This would be one way to optimize vaccine distribution based on effective decision-making (Yang et al., 2021). Inventory at different tiers of the cold chain can be flexed based on manufacturing capability to best meet storage and distribution costs. Adding a coverage index to the hub-and-spoke models helps in choosing which dispensing sites to prioritize first to improve accessibility and meet demand and address the challenges of having specialized storage requirements (Xu et al., 2021). Lastly, considering real-time data on vaccine efficacy and associated costs allows for dynamic decisions on vaccine procurement and distribution strategies, optimizing both health outcomes and economic efficiency (Sripada et al., 2023).

The objective function can consider several elements, from supply chain management aspects (such as production yields and demand uncertainty) to determine optimal selling strategies for vaccines (advance, regular, or dynamic selling). The key takeaway here is that instead of using simplistic methods like cost minimization, the paper accounted for the nature of a vaccine supply chain, specifically in an area with potentially insufficient infrastructure and heterogeneous population (Ekşioğlu et al., 2023) (Trivedi & Gharib, 2023). To make the model more realistic, future studies may want to include a decision variable related to the delay experienced at each stage and its effect on the entire supply chain. This is because time delays could lead to a more complex problem, so the authors could consider heuristic models or learning approaches (Sarmad et al., 2023). Additionally, since multi-tier cold chains are common for public health programs, decision support

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