ISBN: 978-628-96613-3-0. ISSN: 2414-6390. Digital Object Identifier: https://dx.doi.org/10.18687/LACCEI2026.1.1.1453

Simulation and Mathematical Modeling to Support Decision-Making in Urban Vaccination Strategies: A District-Level Study in Lima, Peru

Alvaro Samaniego[1]; Jonatán Rojas[3]; Alexia Caceres[1]; Jackeline Alva[1]

[1]Pontificia Universidad Católica del Perú, Perú, Lima, *alvaro.samaniego@pucp.edu.pe, jrojasp@pucp.pe, alexia.caceres@pucp.pe, jalvaz@pucp.pe*

Abstract– ***Designing effective vaccination strategies remains a significant challenge for urban health systems, particularly in settings characterized by high population density, operational limitations, and pervasive uncertainty. This study addresses this challenge through a simulation-based and mathematical modeling framework aimed at evaluating and comparing alternative vaccination strategies at the district level.***

The proposed approach begins with an optimization formulation based on systems of differential equations derived from a stratified compartmental model, which is subsequently transformed through linearization into a linear programming optimization framework. The model integrates demographic characteristics, vaccination coverage levels, and operational assumptions to assess the impact of different scenarios on overall system performance.

The methodology is applied to a district within the metropolitan area of Lima, Peru—currently home to more than 11 million inhabitants—enabling the mathematical simulation and statistical evaluation of multiple vaccination strategies under varying degrees of service coverage complexity. The results demonstrate that the proposed framework generates actionable quantitative insights to support public health decision-making, facilitating the identification of strategies that enhance coverage efficiency and improve system-wide performance. Overall, the study underscores the value of analytical and modeling tools as effective decision-support mechanisms for vaccination planning in urban contexts across Latin America.

Keywords-- Vaccination strategies, simulation, mathematical modeling, decision support, public health systems.

I. INTRODUCTION

Vaccination is widely recognized as one of the most effective public health interventions for preventing infectious diseases and achieving sustained reductions in population-level morbidity and mortality [1], [2]. Nevertheless, the design and implementation of vaccination strategies in urban environments continue to face substantial challenges, driven by demographic diversity, ethnic heterogeneity, operational constraints within health systems, and the inherent uncertainty of epidemiological dynamics [3]. These challenges are particularly pronounced in large cities within developing countries, where high population density and limited resource availability demand decision-making processes that are both more efficient and grounded in quantitative evidence [4]. In this regard, Lima represents a highly complex case, as it concentrates approximately 33% of the national population.

Within this context, simulation and mathematical modeling tools have gained increasing relevance as support mechanisms for public health planning and policy evaluation. Previous studies have shown that epidemiological models enable the analysis of alternative scenarios prior to implementation, facilitating strategy comparison, impact anticipation, and optimization of healthcare resource allocation [5], [6]. However, in practice, many vaccination campaign decisions still rely on static indicators or simplified assumptions, which constrains the ability to capture the systemic and dynamic effects associated with different intervention strategies [7].

In Latin America, there is a growing need for analytical frameworks that bridge the rigor of mathematical modeling with practical applicability in real-world health systems. The district level constitutes a particularly suitable scale for this type of analysis, as it combines reasonable data availability with sufficient operational complexity to capture relevant interactions among population dynamics, logistics, and health service provision [8]. Despite this potential, empirical applications of simulation and mathematical modeling aimed at evaluating vaccination strategies at the district level remain relatively limited in the literature, especially in urban settings within developing countries.

In response to this gap, the present study proposes a simulation-based and mathematical modeling approach to assess the impact of alternative vaccination strategies in an urban district. The proposed model enables the comparison of different scenarios by incorporating key system variables and operational assumptions, thereby providing a structured basis for supporting decision-making in vaccination campaign planning. The methodology is applied to a district in the city of Lima, Peru, as a representative case of a densely populated urban environment in a developing country with a highly centralized demographic structure. This application allows for the analysis of multiple strategies under varying levels of service coverage complexity.

The main contributions of this study are threefold: (i) the development of a simulation-based analytical model tailored to district-level vaccination planning; (ii) the comparative evaluation of multiple vaccination strategies under different scenarios; and (iii) the generation of quantitative information that strengthens evidence-based decision-making in urban health systems. Taken together, the results highlight the potential of simulation and mathematical modeling tools as practical support mechanisms for the design and evaluation of vaccination strategies in urban contexts across Latin America.

II. State of the Art

The planning of health interventions under operational constraints has traditionally been addressed through a process optimization perspective rooted in Operations Research, a discipline that formalizes decision-making by abstracting real-world processes and constructing mathematical models to allocate scarce resources and assess alternative policies in complex systems [9], [10]. Within this framework, linear programming has been extensively applied due to its ability to represent systems through explicit objective functions and constraint sets, enabling efficient and reproducible solutions for allocation, coverage, and planning problems. Both the objective function and constraints are formulated as linear expressions, with particular attention to inequality constraints, where slack and surplus variables provide insights into system flexibility and dual prices reflect marginal trade-offs [11], [12]. This approach is especially relevant in vaccination campaigns, where vaccine availability, service point capacity, and the prioritization of target groups compete simultaneously for limited system resources.

In parallel, the evolution of data analytics has driven a shift from purely descriptive approaches toward predictive and prescriptive analytics, in which models extend beyond summarizing frequency distributions or central tendencies to actively supporting decision-making through simulation, optimization, and scenario analysis [13], [14], [15]. In healthcare systems, this transition is critical, as it enables movement away from static indicators, such as cumulative coverage, toward the evaluation of dynamic system performance, explicitly incorporating uncertainty, variability, and operational constraints that are central to real-world policy implementation.

A key element linking analytical models to actionable decisions is simulation, which has become a core instrument for examining complex and dynamic health systems. Mathematical simulation models, such as systems of differential equations or stochastic formulations, allow decision-makers to explore "what-if" scenarios prior to implementation, anticipate non-obvious outcomes, and compare intervention strategies under uncertainty [6]. Concurrently, modern epidemiological modeling builds upon classical compartmental frameworks introduced in early mathematical studies of epidemics [16], later extended to capture population heterogeneity and temporal dynamics in disease transmission [17], [5]. Building on these foundations, a substantial body of research has employed simulation-based modeling to assess vaccination strategies, including age-based prioritization, mortality reduction objectives, targeting individuals with comorbidities, interventions in high-risk zones, or transmission mitigation. These studies consistently show that the relative effectiveness of strategies depends on assumptions regarding contact patterns, vaccine supply, efficacy, and implementation conditions [18], [19], [20]. Collectively, this evidence underscores the value of models that explicitly integrate population structure, epidemiological parameters, and operational constraints to support more robust decision-making.

Finally, Geographic Information Systems (GIS) provide a spatial reference framework for the phenomena under analysis and have become increasingly integrated with analytical environments such as ArcGIS and QGIS, often coupled with platforms including Python, Looker Studio, and Power BI. Beyond visualization, GIS tools play an expanding role in the spatial analysis of epidemics and in identifying territorial patterns related to risk, access, and service coverage [21]. Evidence from the COVID-19 pandemic demonstrates that geospatial analytics enhance the ability to map disease spread, territorial inequalities, and access gaps, thereby supporting decisions on resource allocation and deployment in health systems [21]. Nevertheless, despite advances in epidemiological modeling and spatial analysis, there remains a clear opportunity for approaches that integrate simulation and optimization at an operational scale, enabling the evaluation of vaccination policies under realistic scenarios of capacity and coverage.

III. Methodology

This study adopts a simulation-based mathematical modeling approach to support decision-making in the planning of urban vaccination strategies under operational constraints. The proposed methodology integrates epidemiological modeling, optimization techniques, and scenario-based simulation within a unified analytical framework. This integration enables the evaluation and comparison of alternative vaccination strategies while explicitly accounting for population structure, system capacity, and uncertainty.

A. *Problem setting and methodological approach*

This study addresses the problem of designing vaccination strategies in an urban district under epidemiological uncertainty and operational constraints. From an Operations Research perspective, the problem is formulated as a dynamic resource allocation problem, where vaccination decisions interact with the temporal evolution of an epidemic process and with limited system capacity.

The proposed methodology integrates three components:

i. a discrete-time compartmental epidemic model capturing the evolution of the disease;
ii. a linear programming (LP) model representing operational vaccination decisions; and
iii. a scenario-based simulation framework used to evaluate policy alternatives over a finite planning horizon.

This integration enables the explicit coupling of epidemic dynamics with decision variables, allowing a consistent evaluation of vaccination policies in terms of health outcomes and operational performance.

B. Epidemic model formulation

B.1. Population structure and compartments

The total population of the district is partitioned into age-based groups $g \in G$, reflecting heterogeneous infection risk and clinical outcomes. For each group g, the population is divided into the following compartments:

- $S_g(t)$: susceptible individuals,
- $I_g(t)$: infected individuals,
- $V_g(t)$: vaccinated individuals,
- $H_g(t)$: hospitalized individuals,
- $R_g(t)$: recovered individuals,
- $F_g(t)$: deceased individuals.

At each discrete time period t, population conservation holds:

$$N_g = S_g(t) + I_g(t) + V_g(t) + H_g(t) + R_g(t) + F_g(t)$$

The planning horizon is discretized into daily periods $t = 1, \dots, T$, consistent with the operational granularity of vaccination campaigns.

B.2. Disease dynamics

The epidemic dynamics are represented by a system of discrete-time balance equations derived from a compartmental SIR-type structure extended to include hospitalization and mortality. For each group g, the transitions are defined as:

$$S_g(t+1) = S_g(t) - \lambda_g(t) S_g(t) - x_g(t),$$

$$I_g(t+1) = I_g(t) + \lambda_g(t) S_g(t) - \gamma_g I_g(t) - \eta_g I_g(t),$$

$$V_g(t+1) = V_g(t) + x_g(t) - \omega_g V_g(t),$$

$$H_g(t+1) = H_g(t) + \eta_g I_g(t) - \rho_g H_g(t),$$

$$R_g(t+1) = R_g(t) + \gamma_g I_g(t) + \rho_g H_g(t),$$

$$F_g(t+1) = F_g(t) + \mu_g H_g(t),$$

where:

- $x_g(t)$ denotes the number of vaccinated individuals (decision variable),
- $\lambda_g(t)$ is the force of infection for group
- γ_g is the recovery rate,
- η_g is the hospitalization rate,
- ρ_g is the hospital discharge rate,
- μ_g is the mortality rate,
- ω_g captures imperfect vaccine effectiveness.

The force of infection incorporates inter-group contacts:

$$\lambda_g(t) = \beta \sum_{h \in G} C_{g,h} \frac{I_h(t)}{N_h},$$

where represents the contact matrix.

C. Linear programming decision model

To support decision-oriented analysis, the epidemiological model is reformulated into a linear optimization structure. The non-linear dynamics are approximated through linearization techniques, enabling the definition of a linear programming model in which vaccination decisions are explicitly represented as control variables.

The objective function is designed to reflect policy-relevant goals, such as maximizing effective vaccination coverage or minimizing unmet demand within system capacity limits. Constraints represent operational realities, including vaccine availability, service point capacity, and temporal limits on deployment. Slack and surplus variables are incorporated to measure system flexibility, while dual values provide insights into marginal trade-offs associated with constrained resources.

C.1. Decision variables

Vaccination decisions are modeled through continuous non-negative variables:

$$x_g(t) \geq 0 \quad \forall g \in G, t \in T,$$

representing the number of individuals vaccinated in group g at time t.

C.2. Objective function

The LP objective is to minimize the total expected system cost over the planning horizon, including operational vaccination costs and mortality-related economic losses:

$$\min Z = \sum_{t \in T} \sum_{g \in G} c^{vac} x_g(t) + \sum_{t \in T} \sum_{g \in G} c_g{}^{death} \left(F_g(t+1) - F_g(t) \right)$$

where:

- c^{vac} is the unit cost of vaccination,
- $c_g{}^{death}$ represents the economic valuation of mortality for group.

C.3. Operational constraints

The model incorporates key operational constraints:

Vaccination capacity:

$$\sum_{g \in G} x_g(t) \leq C(t) \qquad \forall t \in T,$$

Eligibility constraints:

$$\sum_{t \in T} x_g(t) \leq S_g(0) \qquad \forall g \in G,$$

Non-negativity:

$$x_g(t) \geq 0 \qquad \forall g, t$$

C.4. Linearization and tractability

Although the epidemic dynamics are non-linear, linearity of the LP is preserved by decoupling epidemic evolution and decision optimization within each simulation step. At time t, the state variables $S_g(t), I_g(t)$, are treated as fixed parameters when solving the LP, enabling a sequential linear optimization approach consistent

This optimization-based formulation allows for the systematic comparison of vaccination strategies under consistent assumptions and resource limitations.

D. Simulation Design and Scenario Definition

Simulation is employed as a central mechanism to evaluate the dynamic behavior of the system under alternative strategies. The optimization model is embedded within a simulation environment that iteratively evaluates system performance across predefined scenarios.

The LP model is embedded within a simulation loop that iteratively updates epidemic states and vaccination decisions. For each scenario:

- Epidemic states are initialized.
- The LP is solved to determine $x_g(t)$
- Epidemic states are updated using the dynamic equations.
- Performance indicators are recorded.

Scenarios differ in prioritization weights, capacity levels, and vaccine effectiveness. Outputs include cumulative mortality, time to coverage thresholds, and system utilization. Scenarios are constructed by varying key parameters, including vaccination prioritization rules, coverage targets, and operational capacity levels. For each scenario, the model generates time-dependent outputs that quantify system performance indicators, such as vaccination coverage, utilization of service capacity, and temporal evolution of protected populations.

This simulation-based evaluation enables the assessment of robustness and sensitivity of strategies under uncertainty, supporting evidence-based comparisons among policy alternatives.

E. Data Sources and Assumptions

Model parameters are estimated using official data from the Peruvian Ministry of Health and demographic statistics at district level. The model assumes a closed population, constant parameter values over the horizon, and single-dose immunization for tractability. These assumptions are standard in OR-based epidemic planning models and allow clear interpretation of results. When empirical data are unavailable, assumptions are defined conservatively and consistently across scenarios to preserve internal validity.

All assumptions are explicitly stated to ensure transparency and reproducibility, and the methodology is designed to be adaptable to other urban contexts with similar data availability.

IV. Case Study: Urban District in Lima, Peru

The period of analysis covers the time span from day zero of the pandemic in Peru to the arrival of the first batch of COVID-19 vaccines. The first confirmed case of coronavirus in the country was reported on March 6, 2020 (Yalta, 2020), corresponding to an employee of a local airline who contracted the virus after returning from Europe. In response to the rapid increase in infections, on March 15, 2020, the government declared a nationwide state of emergency, thereby enabling the implementation of extraordinary control measures, most notably the enforcement of mandatory social isolation aimed at reducing population mobility and, consequently, the rate of virus transmission. Initially, this measure was established for a 15-day period; however, due to the lack of significant impact on containing infections, it was extended multiple times.

Fig. 1 Trend in daily deaths as of October 27, 2022.[22]

Although social isolation contributed to reducing transmissibility, it was not sufficient to effectively contain the speed of viral spread, particularly in areas with high population density and in households characterized by a large number of individuals per family.

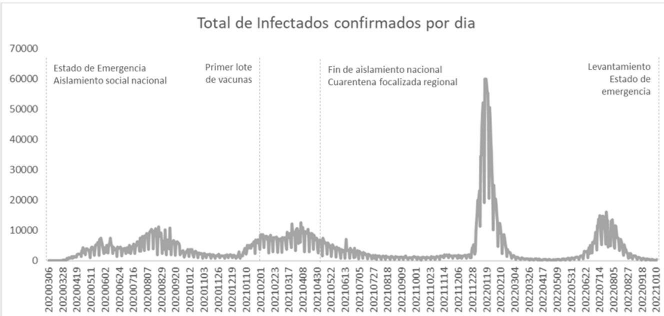

Fig. 2 Evolution of daily confirmed cases as of October 27, 2022.[22]

Direct intervention for infected individuals consisted of hospital-based treatment for patients who exhibited symptoms with the potential to compromise their survival. These patients were managed according to the medical practice available at the time and in line with protocols adopted in other countries, as prior to the development of the first vaccine, clinical interventions were largely limited to palliative treatments aimed at preserving patients' quality of life while their immune systems fought the disease through the generation of endogenous antibodies (See Figure 3 and Figure 4).

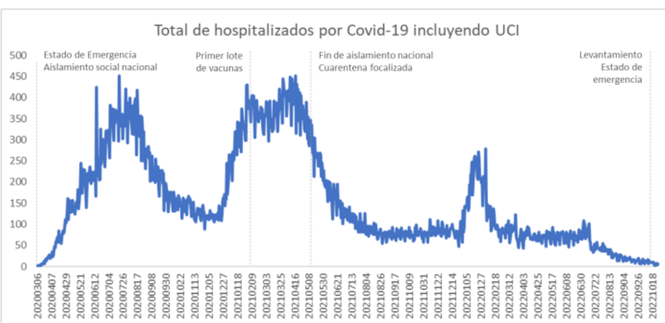

Fig. 3 Trend in daily hospitalizations as of October 27, 2022.[22]

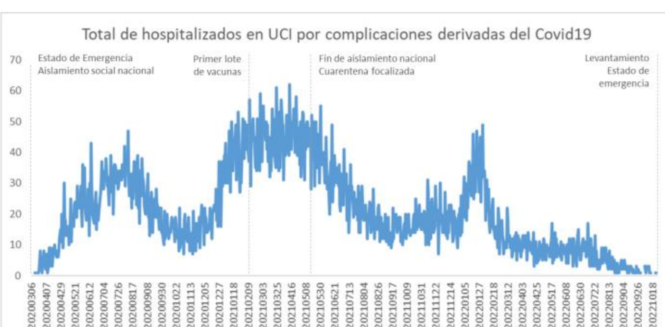

Fig. 4 Trend in ICU hospitalizations as of October 27, 2022.[22]

A. *Strategic relevance of the urban district*

Vaccine distribution was geographically organized primarily according to population size, with priority given to hospitals, health centers, and controlled facilities capable of ensuring cold-chain integrity. In accordance with the guidelines established in the National Vaccination Plan, these sites were selected or adapted based on a set of operational and epidemiological criteria, including population accessibility, local mortality levels, and population density, as well as the availability of infrastructure capable of maintaining cold-chain requirements. Additional considerations included the presence of large, well-ventilated, and adequately illuminated spaces to facilitate physical distancing, access to water supply and sanitation services, and the absence of high-risk congregation areas within the immediate vicinity of vaccination sites.

The vaccination strategy was structured around explicit prioritization criteria. Frontline personnel, particularly healthcare professionals and related workers directly involved in patient care and pandemic response, were prioritized in the initial phase. This was followed by essential workers in both the public and private sectors whose activities were critical to the continuity of daily national operations. Vaccination was subsequently implemented in a sequential manner across age groups, beginning with older populations due to their higher vulnerability and elevated mortality risk associated with comorbidities. Finally, a territorial prioritization framework was applied, incorporating population density, excess mortality, and logistical accessibility as key determinants for allocating vaccination efforts across departments, provinces, and districts (See Figure 5).

Fig. 5 Total number of vaccination centers by department.[23]

The case study focuses on an urban district of Lima, Peru, selected for its strategic relevance in evaluating vaccination planning under severe epidemiological and operational constraints. Lima constitutes the demographic and economic core of the country, concentrating approximately one third of the national population within a highly heterogeneous urban fabric. This concentration amplifies systemic risk during epidemic outbreaks and exposes structural limitations in public health service delivery.

At the district scale, vaccination planning must reconcile competing pressures: high population density, unequal spatial access to health services, constrained operational capacity, and rapidly evolving demand. These conditions make the district an analytically demanding environment, well suited for testing decision-support models that explicitly integrate epidemic dynamics with resource allocation and operational feasibility. Rather than representing an isolated or atypical setting, the district reflects structural features common to large metropolitan areas in developing countries, thereby strengthening the external validity of the analysis.

B. Demographic structure and epidemiological baseline

The population of the district is characterized using official demographic records disaggregated by age groups, consistent with observed differences in infection risk, hospitalization rates, and mortality outcomes. This stratification is essential for capturing heterogeneity in both epidemic impact and vaccination priorities.

The initial epidemiological state is defined using reported data on active infections, cumulative cases, hospital occupancy, and deaths at the start of the planning horizon. These baseline conditions reflect a context of partial susceptibility, limited initial vaccination coverage, and ongoing community transmission, providing a realistic starting point for scenario evaluation. This initialization ensures that simulated trajectories are grounded in observed conditions rather than hypothetical equilibria.

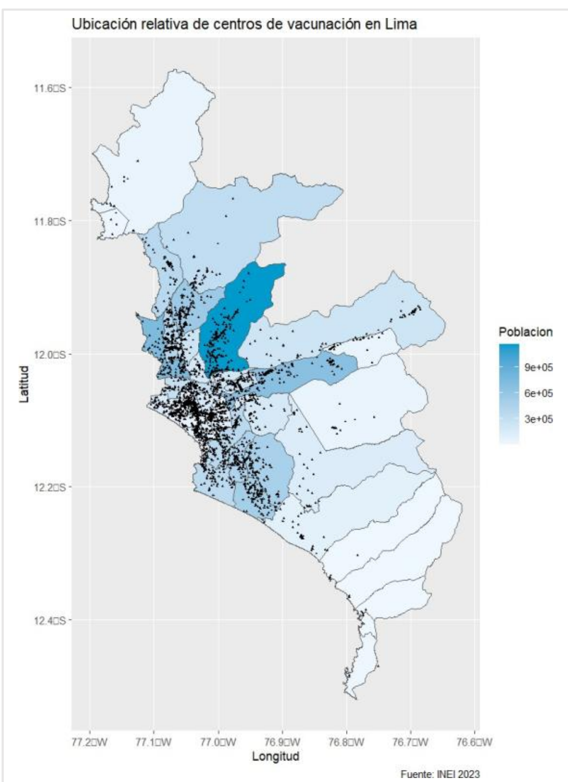

Fig. 6 Relative location of centers versus population density by district.[23]

C. Vaccination system and operational constraints

Vaccination delivery within the district is represented through a network of potential vaccination centers, each characterized by a maximum daily service capacity. Total system capacity is endogenously constrained by staffing availability, physical infrastructure, and logistical coordination, and may vary over time as additional centers are activated.

Operational rules governing the phased opening of vaccination centers are explicitly considered, reflecting institutional and managerial constraints faced by local health authorities. In addition, vaccine supply is assumed to be limited and exogenously determined, requiring prioritization across population groups and time periods.

These features introduce binding constraints that are critical for evaluating the trade-offs between epidemiological effectiveness and operational feasibility, a central concern in vaccination planning.

D. Policy scenarios and comparative evaluation

The case study evaluates multiple vaccination strategies, each representing a distinct policy orientation. Scenarios differ with respect to prioritization criteria (e.g., age-based prioritization versus uniform allocation), vaccination intensity, and assumptions regarding service capacity expansion.

All scenarios are simulated over an identical planning horizon to ensure comparability. Performance is assessed using epidemiological indicators (infections, hospitalizations, mortality), operational metrics (capacity utilization, vaccination throughput), and timing-related outcomes (speed of coverage expansion). This structured comparison enables the identification of dominant and dominated strategies, as well as the characterization of trade-offs inherent to policy choices under constrained resources.

E. Implementation and analytical workflow

The case study is implemented using an integrated simulation–optimization workflow. At each time step, the current epidemic state is updated, the linear programming model is solved to determine feasible vaccination decisions, and the resulting allocations are fed back into the epidemic dynamics. This iterative process generates time-resolved trajectories that capture both short-term operational effects and longer-term epidemiological consequences. The computational structure is sufficiently flexible to accommodate alternative parameterizations and policy assumptions, highlighting the adaptability of the proposed framework to other urban settings.

F. Role of the case study in decision support

Beyond its empirical application, the case study functions as a decision laboratory for exploring the implications of vaccination policies before real-world deployment. By explicitly linking epidemic evolution, operational constraints, and policy objectives, the case study demonstrates how quantitative models can support transparent and evidence-based decision-making in urban public health systems.

V Results and Managerial Insights

A. Model behavior and validation results

The model focuses on three key components. First, transmission rates between compartments are discretized using information obtained from national health data sources. Second, an additional compartment, Hospitalized (H), is incorporated as a subset of the Removed population, capturing individuals whose clinical condition requires hospital care. Third, the analysis is stratified by life stage, given that morbidity among patients aged 60 years and older is substantially higher compared to other age groups, see figure 7.

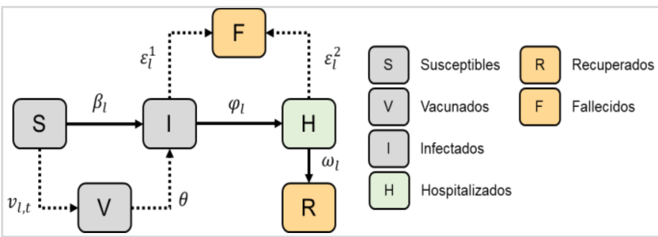

Fig. 7 Discretized model including hospitalized and recovered patients.

The first set of results evaluates the model's ability to reproduce observed epidemic dynamics at the district level. compares reported daily deaths with those generated by the simulation model over the analysis horizon. The close alignment between observed and simulated trajectories indicates that the proposed formulation captures the dominant dynamics of the system under the baseline scenario.

Minor deviations observed at specific time points can be attributed to exogenous factors not explicitly modeled, such as behavioral changes or reporting delays. Nevertheless, the overall consistency between real and simulated outcomes supports the suitability of the model as a decision-support tool rather than a purely predictive instrument.

This validation step is critical, as it establishes confidence in the use of the model for comparative evaluation of vaccination strategies under alternative operational conditions.

B. Operational dynamics and capacity deployment

Figure 8 and table I illustrates the evolution of the number of vaccination centers activated over time. Results show a phased deployment pattern, driven by operational constraints on opening capacity rather than by epidemiological demand alone. This highlights a key insight: in highly constrained urban settings, vaccination performance is not solely limited by vaccine availability but also by the system's ability to expand service capacity in a timely manner.

TABLE I
Results of status variables, by age group, day 70

Age range	Day	S	I	V	F	H	R
0 – 11	70	0	8	42,775	7	1	83
12 – 17	70	0	61	23,909	6	1	47
18 – 29	70	0	513	55,648	139	3	143
30 – 59	70	0	140	114,710	1,011	4	180
60 - 200	70	0	5	49,051	496	1	31

The simulation reveals periods where vaccination demand exceeds operational capacity, generating backlogs that delay coverage expansion. These findings emphasize the importance of synchronizing capacity deployment decisions with epidemic dynamics to avoid inefficiencies that reduce the overall impact of vaccination campaigns.

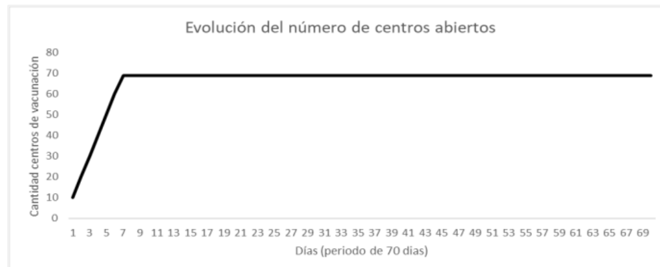

Fig. 8 Evolution of the number of centers opened up to day 70.

During the initial 70-day period, the total costs of setting up vaccination centers amounted to S/. 22,556,400, while the opportunity costs of mobilizing people amounted to S/544,227, and the estimated costs per death for all age groups totaled S/. 91,225,800, with a minimum total cost of S/.114,326,427.

C. Epidemiological outcomes across strategies

The total evolution of COVID deaths obtained from the model was compared with the same 70-day replica starting on February 7, 2020. The comparison of vaccination strategies demonstrates significant differences in epidemiological outcomes shown in Figure 9, even when total vaccine supply remains constant. Strategies that prioritize high-risk or older age groups consistently reduce cumulative mortality more effectively than uniform allocation approaches, as evidenced by the age-disaggregated mortality patterns shown in Figure 10.

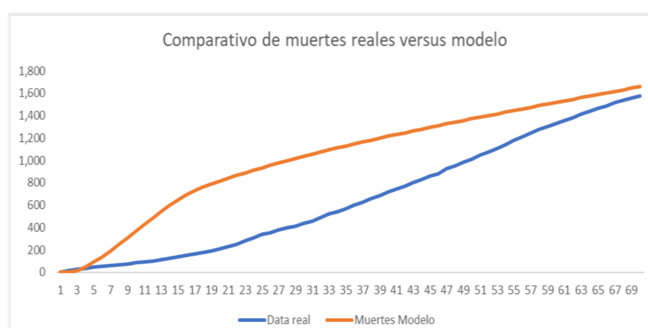

Fig. 9 Deaths in reality versus model, by day.

These results confirm that prioritization rules play a critical role in shaping health outcomes, particularly in early stages of vaccination campaigns when supply and capacity are limited. Importantly, the benefits of prioritization diminish as coverage expands, suggesting that adaptive strategies may outperform static policies over longer horizons.

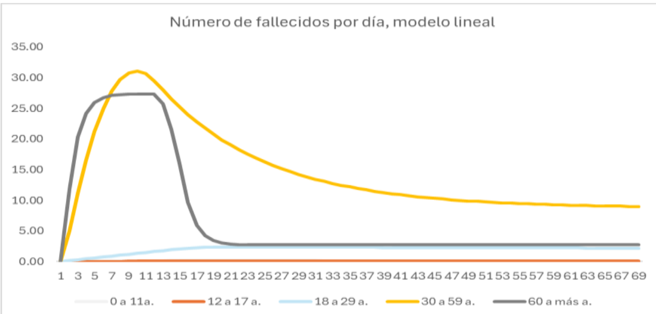

Fig. 10 Deaths in the model by age group, by day.

D. Economic and system-level performance

A comparison was also made against the model's three main impact indicators: location costs, opportunity costs per person (movements, etc.), and the discounted cost of deaths per day. Analyzing the district of Lima as an isolated entity, it can be seen that total costs are impacted by the costs of deaths in the first 10 - 15 days, due to the fact that there are still many individuals susceptible to infection who are not vaccinated. Thereafter, the total cost curve decreases significantly.

Figure 11 presents the evolution of total system costs over time, decomposed into operational costs and mortality-related economic losses. While prioritization strategies may incur slightly higher operational costs due to targeted deployment, they achieve substantially lower mortality-related losses, resulting in lower total system costs over the planning horizon.

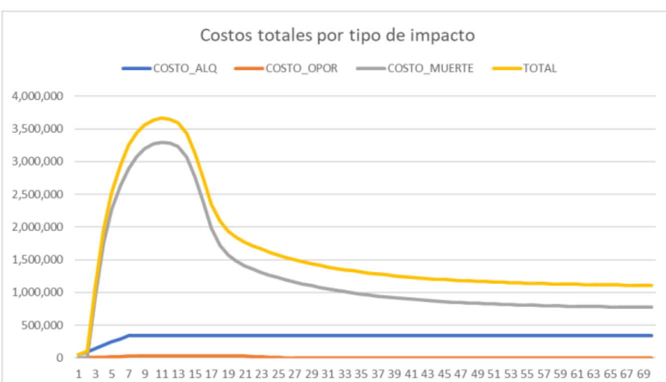

Fig. 11 Total costs by type of impact, per day.

This trade-off underscores a central contribution of the proposed framework: by explicitly linking epidemiological outcomes with economic impacts, the model enables decision-makers to evaluate vaccination strategies using integrated performance metrics rather than isolated indicators.

E. Spatial insights and service accessibility

The spatial configuration of vaccination centers, illustrated in Figures 12 and 13, provides additional insights into service accessibility and geographic equity. The optimized deployment of centers reduces average travel distances relative to initial configurations, improving access for large segments of the population without requiring a proportional increase in infrastructure. These spatial results reinforce the importance of considering geographic structure in vaccination planning, particularly in dense urban environments where small changes in location can have large effects on accessibility and utilization.

The initial allocation of vaccination centers should follow an order that prioritizes coverage of the largest population per square meter. However, by not following a multi-objective criterion, it is likely that the available location for opening new centers will not be used optimally.

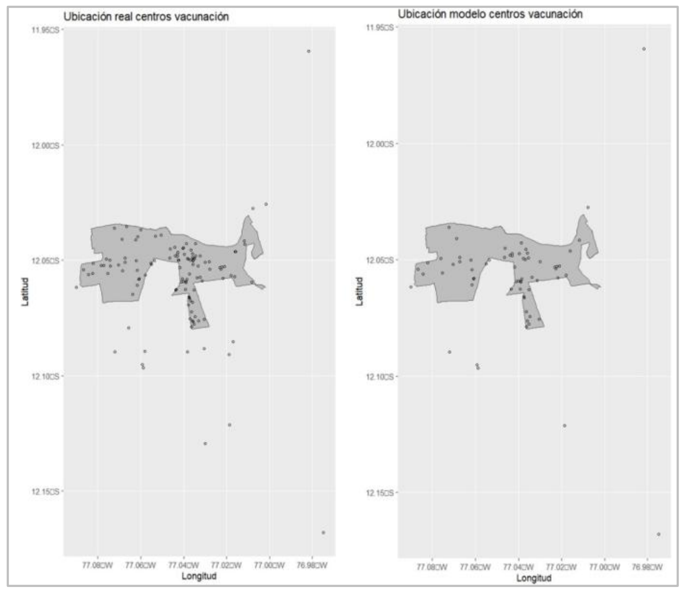

Fig. 12 Initial and final locations (model) of vaccination centers in Lima.

Comparing this with the centers that remain open on the last day of the simulation, it can be confirmed that, under a linear programming approach with a series of assumptions that differ from the actual behavior of the pandemic interaction, there are fewer centers open.

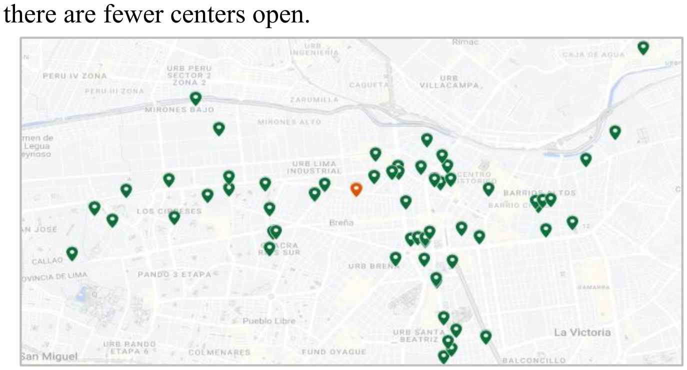

Fig. 13 Location of vaccination centers (green) and centroid (red) of Lima.

F. Managerial and policy implications

From a managerial perspective, the results demonstrate that vaccination planning should be approached as a dynamic resource allocation problem rather than as a static coverage exercise. Decisions regarding capacity expansion, prioritization, and spatial deployment interact non-linearly with epidemic dynamics, producing outcomes that cannot be inferred from static indicators alone.

For policymakers, the findings suggest that early investments in operational capacity and targeted prioritization can yield disproportionate benefits in terms of reduced mortality and system-wide efficiency. The proposed framework offers a structured mechanism for testing such decisions ex ante, reducing reliance on ad hoc judgment under crisis conditions.

G. Robustness and decision relevance

Sensitivity analyses indicate that while absolute outcomes vary with key parameters such as vaccine effectiveness and transmission rates, the relative ranking of strategies remains stable across a wide range of conditions. This robustness strengthens the decision relevance of the results, supporting their use in real-world planning contexts. Overall, the results demonstrate that integrating simulation, optimization, and spatial analysis provides actionable insights that extend beyond descriptive modeling, positioning the framework as a practical tool for supporting vaccination policy in complex urban systems.

G.1. Sensitivity of Vaccine Effectiveness on Total Costs and Mortality

A sensitivity analysis was conducted to examine the impact of vaccine ineffectiveness on total system costs and mortality outcomes. By simulating a range of vaccine ineffectiveness levels against COVID-19, the results indicate that, within the structure of the proposed model, total mortality and associated economic costs exhibit an approximately linear response to changes in vaccine effectiveness.

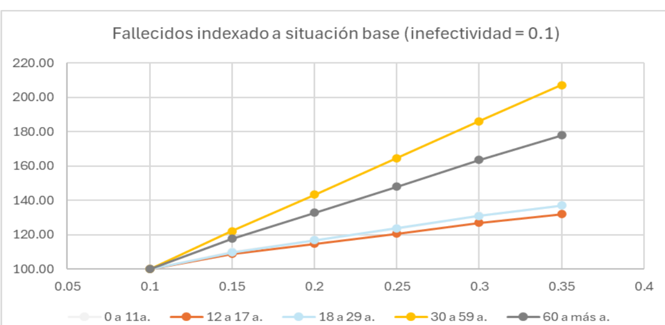

Fig. 14 Indexed variation in deaths by age group.

The analysis further reveals that the effects of reduced vaccine effectiveness are not evenly distributed across the population. The most pronounced impacts are observed in age groups with the largest susceptible populations (30–59 years) and in those with the highest mortality risk (60 years and older). These findings highlight the critical role of vaccine effectiveness in shaping both epidemiological and economic outcomes, particularly in demographic segments that drive transmission intensity and severe health consequences (see figure 14).

G.2. Sensitivity of Vaccination Center Capacity on Total Costs and Mortality

A sensitivity analysis was performed to assess the effect of daily vaccination capacity per center on total system costs and mortality outcomes. Simulation results indicate a markedly non-linear relationship between vaccination capacity and total costs, characterized by an exponential increase as capacity levels expand. This behavior reflects the operational and logistical costs associated with scaling service delivery beyond baseline capacity. In contrast, the relationship between vaccination capacity and mortality reduction is approximately linear, mirroring the pattern observed in the vaccine effectiveness sensitivity analysis. Incremental increases in daily capacity lead to proportional decreases in the number of deaths, suggesting diminishing marginal epidemiological returns relative to the rapidly increasing operational costs. These results emphasize the importance of balancing capacity expansion with cost efficiency when designing vaccination strategies (see figure 15).

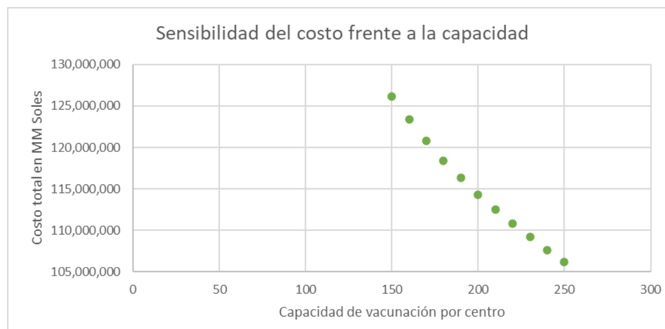

Fig. 15 Sensitivity of total cost to vaccination capacity.

G.3. Sensitivity of the Maximum Number of Vaccination Centers Opened per Day

A sensitivity analysis was conducted to evaluate the impact of varying the maximum number of vaccination centers that can be opened per day on total system costs. Simulation results reveal an asymptotic cost behavior as the daily opening capacity increases. Specifically, beyond a threshold of approximately eight newly opened centers per day, additional capacity expansion yields progressively smaller reductions in total costs. This asymptotic trend indicates that, after a certain operational scale is reached, the marginal benefits of accelerating center deployment diminish, while fixed and variable costs continue to accrue. The results, illustrated in figure 16, suggest the existence of an operational saturation point beyond which further expansion does not translate into meaningful system-wide efficiency gains. These findings highlight the importance of identifying optimal deployment thresholds rather than pursuing unrestricted capacity growth.

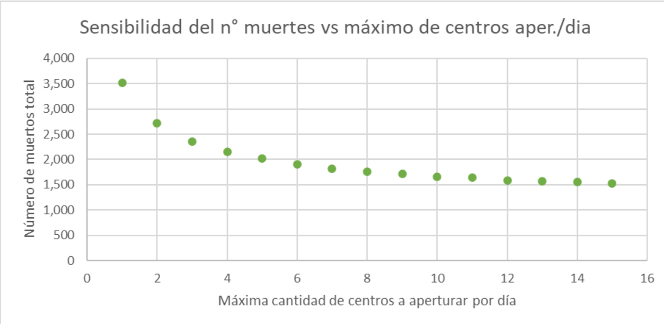

Fig. 16 Sensitivity of total deaths to maximum daily openings of centers.

G.4. Sensitivity of the number of vaccination days prioritized by age group

Making a change to the model that forces the highest-risk age group (60 years and older) to be served in the first 15 days, the second-highest-risk group (30 to 59 years) to be included in the following 15 days, and all age groups to be served during the rest of the time. The impact is slightly reduced for the most critical range, but greatly affects the second most critical range.

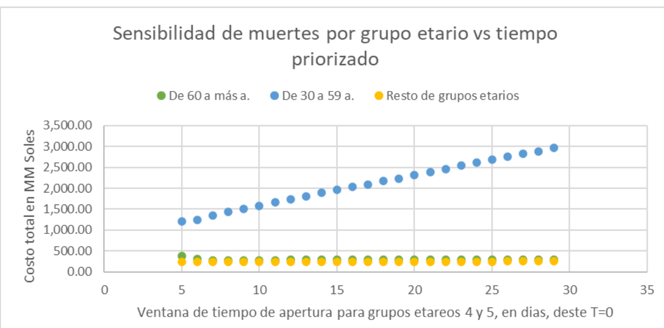

Fig. 17 Sensitivity of the number of deaths to prioritization time for critical age groups.

VI. Conclusions

This paper shows that vaccination planning in complex urban settings can be effectively supported through an integrated simulation–optimization framework. By coupling a discrete-time epidemic model with a linear programming formulation, the approach captures key interactions between epidemiological dynamics and operational constraints. The case study demonstrates that targeted and coordinated strategies outperform uniform capacity expansion in terms of mortality reduction and cost efficiency. Overall, the results highlight the value of Operations Research tools for evaluating vaccination policies under realistic urban conditions.

References

[1] World Health Organization. Immunization Agenda 2030: A Global Strategy To Leave No One Behind. WHO, 2020. https://www.who.int/publications/m/item/immunization-agenda-2030-a-global-strategy-to-leave-no-one-behind

[2] World Health Organization. Andre, F. E., Booy, R., Bock, H. L., Clemens, J., Datta, S. K., John, T. J., Lee, B. W., Loleka, S., Peltola, H., Ruff, T. A., SSantosham, M., & Schmitt, H. J. Vaccination greatly reduces disease, disability, death and inequity worldwide. Bulletin of the World Health Organization. Volumen 86(2), pages 140 – 146. 2008. https://doi.org/10.2471/BLT.07.040089

[3] Fine, P., Eames, K., & Heymann, D. L. Herd immunity: A rough guide. Clinical Infectious Diseases. 2011. Volumen 52(7), pages 911 – 916. https://doi.org/10.1093/cid/cir007

[4] Pan American Health Organization. Immunization in the Americas: 2021 Summary. 2021. https://iris.paho.org/handle/10665.2/54858

[5] Keeling, Matt J., and Pejman Rohani. Modeling Infectious Diseases in Humans and Animals. Princeton University Press, 2008. https://doi.org/10.2307/j.ctvcm4gk0

[6] Vynnycky, E., & White, R. G. An introduction to infectious disease modelling. Oxford University Press. 2010.

[7] Halloran, M. E., Longini, I. M., & Struchiner, C. J. Design and analysis of vaccine studies. Springer. 2010. https://doi.org/10.1007/978-0-387-68636-3

[8] World Health Organization. Guidance on development and implementation of a national deployment and vaccination plan for vaccines against pandemic influenza and other respiratory viruses of pandemic potential. [8] World Health Organization 2023. https://iris.who.int/server/api/core/bitstreams/63e13704-4367-45e7-8c21-0b7e49405c1c/content

[9] Winston, W. L. Operations research: Applications and algorithms. Thomson. 2004.

[10] Taha, H. A. Operations research: An introduction (10th ed.). Pearson. 2017.

[11]Dantzig, G. B. Linear programming and extensions. Princeton University Press. 1963.

[12]Bertsimas, D., & Tsitsiklis, J. N. Introduction to linear optimization. Athena Scientific. 1997.

[13]Davenport, T. H., & Harris, J. G. Competing on analytics: The new science of winning. Harvard Business Review Press. 2007.

[14]Shmueli, G., & Koppius, O. R. Predictive analytics in information systems research. MIS Quarterly 2011, Volume 35(3), pages 553 – 572. https://doi.org/10.2307/23042796

[15]Waller, M. A., & Fawcett, S. E. Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. Journal of Business Logistics, Volume 34(2), pages 77 – 84. 2013. https://doi.org/10.1111/jbl.12010

[16]The Royal Society. Kermack, W. O., & McKendrick, A. G. A contribution to the mathematical theory of epidemics. Proceedings of the Royal Society of London. 1927. Volume 115, Issue 772, 700 – 721. https://doi.org/10.1098/rspa.1927.0118

[17]Anderson, R. M., & May, R. M. Infectious diseases of humans: Dynamics and control. Oxford University Press. 1991. https://doi.org/10.1093/oso/9780198545996.001.0001

[18]Halloran, M. E., Longini, I. M., & Struchiner, C. J. (2010). Design and analysis of vaccine studies. Springer, New York, 2010. Volume 67, Issue 1, 2010, Pages 326 – 327. https://doi.org/10.1111/j.1541-0420.2011.01551.x

[19]Bubar, K. M., Reinholt, K., Kissler, S. M., Lipsitch, M., Cobey, S., Grad, Y. H., & Larremore, D. B. Model-informed COVID-19 vaccine prioritization strategies by age and serostatus. Science. 2021. Volume 371(6532), pages 916 – 921. https://doi.org/10.1126/science.abe6959

[20]Matrajt, L., Eaton, J., Leung, T., Dimitrov, D., Schiffer, J. T., Swan, D. A. & Janes, H. Optimizing vaccine allocation for COVID-19 vaccines shows the potential role of single-dose vaccination. 2021. Nature Communications, Volume 12. https://doi.org/10.1038/s41467-021-23761-1

[21]Franch-Pardo, I., Napoletano, B. M., Rosete-Verges, F., & Billa, L. Spatial analysis and GIS in the study of COVID-19: A review. Science of The Total Environment. 2020. Volume 739, 140033. https://doi.org/10.1016/j.scitotenv.2020.140033

[22]Ministerio de Salud. Sala Situacional Covid 19. 2022. https://covid19.minsa.gob.pe/sala_situacional.asp
Ministerio de Salud. Documento Técnico: Plan Nacional Actualizado de Vacunación contra la Covid-19. Lima, Perú. 2021.