Decision Analytics Group Project : Vaccine Distribution Optimization for Montréal's COVID-19 Response

Group 3855 - 1

Presented to
Professor Javad Nasiry

By
Delisle, Audrey - 261142504
DeSilva, Dhevin - 261177497
Belmadani, Samia - 260927564
Lagarde, Tiffany - 261142798
Palummo, Julien - 260946408

MGSC 662 Decision Analytics - Section 076

McGill University - Desautels Faculty of Management
Thursday November 23rd 2023

Table of Contents

1. Introduction

1. 1 Project Summary

This project focuses on developing a programming model to optimize the distribution of COVID-19 vaccines. The core of the model revolves around efficiently allocating vaccine supplies from multiple suppliers to various vaccination centers, taking into account factors such as supply limits, demand at different vaccination centers, transportation costs, and the urgency dictated by COVID-19 case intensity in different neighborhoods. The model is structured to minimize the overall cost, which includes transportation costs, the cost of purchasing vaccines, and penalties associated with unmet demand and insufficient response to high-intensity COVID-19 areas. It utilizes Gurobi Optimizer, a powerful tool for solving linear and integer optimization problems, to find the optimal distribution strategy that meets the demand as effectively as possible while minimizing costs.

1.2 Project Goals

The primary goals of this project are:

Efficient Resource Allocation: To ensure that vaccine distribution is carried out in a manner that maximizes the use of available resources, such as vaccine supplies and transportation capacity.

Cost Minimization: To reduce the overall cost of the vaccine distribution process, including the expenses incurred through transportation and procurement.

Addressing Urgency and Need: To prioritize areas with high COVID-19 case intensity, thereby aligning the distribution efforts with public health needs and urgency.

Model Flexibility: To create a model that can adapt to changing circumstances, such as fluctuations in supply, demand, and pandemic intensity.

1.3 Relevance of Topic Choice

We chose to focus on COVID-19 for our project because it has resurfaced in Quebec in the early fall of 2023, with new variants and booster shots being introduced to combat them. This topic holds significant relevance in the present context. The COVID-19 pandemic has left a global impact, and effectively distributing vaccines is crucial for managing and ultimately overcoming this health crisis. This project addresses the challenge of optimizing limited healthcare resources, a pressing issue during a pandemic. It also demonstrates how data and mathematical modeling can aid in making vital decisions that impact public health and safety. Moreover, the principles and methods applied here not only pertain to COVID-19 but also offer valuable insights for broader applications in healthcare logistics and emergency response planning.

2. Problem Description

2.1 Problem Description

In the midst of the COVID-19 pandemic, the city of Montreal faces a critical challenge in distributing vaccines efficiently across its healthcare network. The complexity of this task is heightened by the intricate web of suppliers, vaccination centers, and diverse neighborhoods, each with unique demands and constraints. The vaccine supply chain is a long and complex process, hence for this project, we can only focus on certain parts. Please view Appendix A to see the whole supply chain and the areas of focus for our project.

Our problem falls under the category of an 'Unbalanced Inventory Problem.' We aim to optimally distribute a weekly vaccine supply over five weeks while minimizing transportation costs and penalties for unmet demand. Our total supply of 33,815 vaccines falls slightly short of the total demand of 35,181, making resource optimization crucial. The challenge is further complicated by the changing demand and urgency levels observed over the weeks from October to November 2023 (t=0-4), highlighting the dynamic nature of our allocation strategy. Below, we have described the key variables and challenges present in our problem.

2.2 Contextual Overview of Key Variables

Vaccination Centers (j): Montreal has 17 designated vaccination centers, strategically placed across the city. These centers are the focal points for vaccine administration, catering to the local population's needs.

Neighborhoods (n): The city comprises 9 distinct neighborhoods. Each neighborhood has its own demographic and health profile, influencing the demand for vaccines and the urgency of delivery. One neighborhood can have multiple vaccination centers.

Suppliers (i): The vaccine supply chain is supported by 6 key suppliers, each with different vaccine types, capacities, and cost structures.

Time Frame (t): The distribution plan is evaluated over a series of 5 consecutive weeks, in the months of October to November. This time series approach allows for dynamic adjustment and responsiveness to changing demands and supply conditions.

2.3 Key Challenges:

Demand vs. Supply: With limited vaccine supplies, one of the major challenges is to ensure that the available doses are distributed in a manner that maximizes public health benefits while meeting the demand as much as possible.

Diverse Pricing: Each supplier offers vaccines at different prices, adding a financial dimension to the allocation problem. The goal is to balance cost-effectiveness with the urgency and demand of the vaccination effort.

Transportation Logistics: The cost and logistics of transporting vaccines from suppliers to vaccination centers vary. Efficient routing and distribution are crucial to minimize transportation expenses and ensure timely delivery.

Urgency and Public Health Priorities: Some neighborhoods, particularly those with high COVID-19 case rates or vulnerable populations, require more urgent attention. Prioritizing these areas, while ensuring fair distribution across the city, is a delicate balancing act.

2.4 Objective

The objective is to optimize the distribution of vaccines by minimizing the total cost, which encompasses purchasing vaccines from suppliers, transportation expenses, and penalties associated with unmet demand, especially in high-priority areas. This model is not only a tool for immediate pandemic response but also a blueprint for handling similar large-scale public health crises in the future. By analyzing various scenarios and constraints, the model provides insights into strategic decision-making and resource allocation in public health logistics.

3. Data Collection

3.1 Data Sources

Below are the websites we used for data collection. Please view Appendix B for some examples.

1. Gov Quebec: Population for neighborhoods in Montreal from https://www.quebec.ca/
2. Stats Canada: Age distribution in Canada: https://www150.statcan.gc.ca/
3. Stats Canada: Target Immunization rates Canada: https://www150.statcan.gc.ca/
4. Stats Canada: Historical Vaccination Rates: https://www150.statcan.gc.ca/
5. Stats Canada: High-risk age boundaries: https://www150.statcan.gc.ca/
6. Health Infobase Canada: Number of weekly COVID-19 cases: https://health-infobase.canada.ca
7. Health Infobase Canada: Number of weekly COVID-19 deaths: https://health-infobase.canada.ca
8. Statista: Vaccine purchase costs: https://www.statista.com/statistics/
9. Github: Weekly vaccine supply coming to Canada: https://github.com/ccodwg/Covid19Canada
10. Stats Canada: Initial supply agreement of each vaccines for Canada: https://www.canada.ca
11. Stats Canada: Population estimates: https://www150.statcan.gc.ca
12. Gov Quebec: Region population estimates: https://statistique.quebec.ca/

3.2 Data Collected

1. Geographic Data for Vaccination Center Locations and Corresponding Neighborhoods: Used Google Maps to locate vaccination centers and the coordinates.

2. Weekly Count of COVID-19 Cases: This data provides a time-series record of the weekly count of confirmed COVID-19 cases within the Montreal region, serving as a fundamental indicator for gauging the prevalence of the disease.

3. Weekly Count of COVID-19-Related Fatalities: This dataset presents the weekly count of fatalities attributed to COVID-19 in the Montreal region, a crucial metric for assessing the pandemic's impact.

4. Calculation of COVID-19 Fatality Rate: The COVID-19 fatality rate is determined by calculating the ratio of the number of COVID-19-related fatalities to the number of confirmed cases within a given week. The formula is as follows: $Fatality\ Rate\ =\ Weekly\ Fatalities\ /\ Weekly\ Cases$

5. Estimation of Vaccine Demand: This formula computes the projected demand for COVID-19 vaccines, accounting for factors such as population size, vaccination objectives, historical vaccination rates, the high-risk population segment, and the impact of the fatality rate on demand.

$$
\begin{aligned}
Vaccine\ Demand\ =\ &(Total\ Population\ *\ Target\ Vaccination\ Rate\\
&*\ Actual\ \%\ of\ Population\ Vaccinated\ per\ Season\ \ *\ \%\ of\ Population\ Classified\ as\ High\ Risk)\\
&+\ (Total\ Population\ *\ Target\ Vaccination\ Rate\ *\ Actual\ \%\ of\ Population\ Vaccinated\ per\ Season\\
&*\ \%\ of\ Population\ Classified\ as\ High\ Risk\ *\ Fatality\ Rate)
\end{aligned}
$$

6. Population Demographics : Total Population: Population demographics data was sourced from the Canadian government website, providing the total population figure for the Montreal region. This data serves as a foundational parameter for vaccine demand estimation and distribution planning.

7. Vaccination Objective : Target Vaccination Rate: The target vaccination rate, obtained from the Canadian government website, defines the desired percentage of the population to be vaccinated against COVID-19, serving as a strategic benchmark.

8. Historical Vaccination Rates : Actual Percentage of Population Vaccinated per Season: Historical data on vaccination rates during previous flu seasons, sourced from the Canadian government website, informs the anticipated COVID-19 vaccination rates and guides planning efforts.

9. Demographic Breakdown : Percentage of Population Classified as High-Risk: Leveraging age distribution data and predefined criteria for high-risk categorization, this metric quantifies the proportion of the population deemed high-risk, contributing to the computation of vaccine demand.

10. High-Risk Population Criteria Definition: The definition of high-risk population, obtained from official sources, articulates the criteria for identifying individuals at an elevated risk of severe COVID-19 illness or complications.

11. Calculation of supply of each vaccine: Employed the Github dataset for monitoring the weekly vaccine arrivals in Canada. To determine the vaccine supply for Quebec, we calculated it based on the population proportion from Statistics Canada, specifically the percentage of vaccines allocated to Quebec compared to the rest of Canada (23%). To determine the vaccine supply for each region in our model, we calculated it based on the population proportion from the government of Quebec website. This calculation of supply also incorporated the initial vaccine agreement with Canada to establish the weighted proportion of each vaccine supplier in the supply.

4. Mathematical Formulation

4.1 Parameters & Rationale

The mathematical formulation of the vaccine distribution problem in Montreal involves several key components, each representing a crucial aspect of the logistical and decision-making challenges:

- Vaccine Purchase Cost (p_i): The cost of purchasing each vaccine from supplier i.
- Transportation Cost (t_{ij}): The cost of transporting vaccines from each supplier i to each vaccination center j.
- c_n: Number of Covid - 19 cases in neighborhood n
- d_n: Number of Covid - 19 deaths in neighborhood n
- α: Weighting factor representing the importance of Covid-19 cases (0.05)
- β: Weighting factor representing the importance of Covid-19 deaths (0.1)
- h: The penalty incurred for each unit of unmet demand in a neighborhood. Medical costs associated with 1 person catching Covid (1,000)
- $u_{n,t}$: Urgency penalty taking into consideration deaths and cases $u_{nt} = \alpha \cdot c_{nt} + \beta \cdot d_{nt}$
- $D_{n,t}$: Vaccine demand (based on population) in neighborhood n at time t
- $S_{i,t}$: The available number of vaccines from each supplier is at each time period t.

The rationale behind our parameter choices for 'α' (0.05), 'β' (0.1), and 'h' (1,000) is based on various factors. To determine the penalty associated with unmet demand ('h'), we referred to an article estimating the average cost for COVID-19 ICU patients, which amounted to more than $50,000[1]. We assumed this to be the cost of one person contracting a severe case of COVID-19. Next, we considered the likelihood of hospitalization, which we found to be approximately 20% for individuals who contract

[1] The Canadian Press. (Sep 09, 2021). Average cost for COVID-19 ICU patients estimated at more than $50,000: report. CBC News. https://www.cbc.ca/news/health/cihi-covid19-canada-hospital-cost-1.6168531

COVID-19[2]. Assuming that around 10% of unvaccinated individuals may catch COVID-19, we calculated the 'h' penalty to be $1,000, considering these probabilities (50,000*0.2*0.1).

Regarding 'α' and 'β,' which represent the weighting factors for cases and deaths, we aimed to strike a balance between their importance. Deaths were considered more critical than cases, leading us to assign a higher weight to 'β' (0.1) and a lower weight to 'α' (0.05). We wanted to ensure that it did not exceed the general penalty ('h'). To achieve this, we estimated the urgency penalty to be around 20-40% of the general penalty, equivalent to approximately $200-$400. Through trial and error, we determined that 'α' and 'β' should be approximately 0.1 to align with this urgency penalty scale, resulting in our selected values of 0.05 for 'α' and 0.1 for 'β.' Consequently, the additional urgency penalty demand amounted to approximately $355, completing our parameter choices.

4.2 Decision Variables

In our optimization model, we introduce the decision variables denoted as Xijt , where each variable represents the quantity of vaccines transported from supplier i to vaccination center j during a specific time period t. The time periods span five consecutive weeks, commencing from October 15th to November 18th.

4.3 Objective Function

The objective function in our optimization model, denoted as Z, encompasses two primary components: the procurement and transportation costs section and the unmet demand penalties, both of which contribute to the overall objective of minimizing the total cost while ensuring timely and effective vaccine allocation.

Objective Function: $$Z=\sum_{i,j,t}(p_i+t_{i,j})\times x_{ijt}+\sum_{n,t}(h+u_{n,t})\times(D_{n,t}-\sum_{i\in I(n),j}x_{ijt})$$

In the first section, the objective function considers the procurement and transportation costs. Here, we aim to minimize the expenses incurred by acquiring vaccines from different suppliers (p_i) and transporting them to various vaccination centers ($t_{i,j}$). The summation ($\sum_{i,j,t}(p_i+t_{i,j})\times x_{ijt}$) represents the cumulative cost associated with purchasing vaccines and their transportation, spanning across suppliers, vaccination centers, and time periods. This part of the objective function emphasizes cost-effectiveness in our allocation strategy.

[2] Bernanke, J. (2021, April 9). What's the risk of getting hospitalized with COVID? https://covid-101.org/science/whats-the-risk-of-getting-hospitalized-with-covid/

The second section of the objective function addresses the penalties associated with unmet vaccine demand. It consists of two components: a general penalty cost (h) and an urgency penalty (u). The general penalty (h) is applied to unmet demand in each neighborhood ($D_{nt}-\sum_{i\in I(n),j} x_{ijt}$) and reflects the overall cost attributed to individuals not receiving vaccinations (view parameter rationale). Additionally, the urgency penalty (u) accounts for the specific demand urgency, allowing us to assess the consequences of delayed vaccinations and prioritize critical areas. The urgency factor (u_{nt}) is calculated as $\alpha \cdot \text{Cases}_{nt}+\beta \cdot \text{Deaths}_{nt}$, where α and β are weighting factors representing the importance of COVID-19 cases and deaths, respectively. By incorporating these penalty terms, the objective function ensures a balance between minimizing costs and meeting demand, thus guiding our optimization efforts effectively.

4.4 Constraints

1) Supply Constraints: Ensure that the total vaccines supplied by each supplier to each vaccination center at each time period do not exceed the available supply.

$$\sum_{j,t} \mathbf{X}_{i,j,t} \leq \mathbf{Supply}_{i,t}$$

2) Demand Constraints: Ensure that the total vaccines distributed to each neighborhood's vaccination centers at each time period do not exceed the total demand for vaccines in that neighborhood.

$$\sum_{i\in I(j)} \mathbf{X}_{ijt} \leq \mathbf{Demand}_{nt}$$

3) Proportion of demand met: Ensure that at least 10% of the demand in each neighborhood is met by the vaccines distributed at each time period.

$$\sum_{i,j} \mathbf{X}_{i,j,t} \geq \mathbf{0.1 * Demand}_{n,t}$$

4) Non-negativity Constraints: Ensure that the number of vaccines transported from each supplier to each vaccination center at each time period is non-negative.

$$\mathbf{X}_{ijt} \geq \mathbf{0}$$

5) Supply Less Than Demand Indicator Constraints: Introduce binary variables to indicate if the total supply is less than total demand at each time period. Ensure that if this indicator is 1, the total supply is indeed less than demand, and vice versa. (Binary variable supply_less_than_demandt)

6) Use All Supply When Less Indicator Constraints: Ensure that if the supply is less than demand at a time period, all available supply is used, and no vaccines remain unused.

$$\sum_{i,j} \mathbf{X}_{i,j,t} = \mathbf{Total\_supply}_t\mathbf{, when\ supply\_less\_than\_demand=1}$$

7) Equal Distribution Constraints: Ensure that vaccines are equally distributed among vaccination centers within each neighborhood at each time period.

$$\sum_{i,t} \mathbf{X}_{i,j,t} = {}^{\mathbf{total\_vaccines\_for\_neighbourhood}} / {}_{\mathbf{num\_centers\_in\_neighbourhood}}$$

5. Numerical Implementation and Results

5.1 Problem Formulation in Modeling Language

The optimization model developed for Montreal's COVID-19 vaccine distribution employed Python and the Gurobi Optimizer. Key steps in the process included importing critical data from an Excel file, then meticulously formatting this data for optimization modeling. We then added our variables, our objective function and our constraints into the code (addVars, model.optimize, addConstr). Next, we printed the solution and generated a sensitivity analysis, which assessed the model's adaptability to changing supply-demand dynamics and identified potential surplus or shortage areas.

5.2 Solutions

Our optimization model, executed using the Gurobi Optimizer, successfully devised a strategic plan for distributing COVID-19 vaccines across Montreal. The model's optimal solution led to a minimum cost of $13,996,643.87, with a significant part of this amount, $8,541,303.01, allocated to procurement and transportation costs. We then wanted to analyze if this answer was logical in a real-world context. As of the Canadian government's budget for Covid-19 in fiscal year 2021-22, the main estimates came up to 22.1 billion dollars (this does not include wage subsidies).[3] They did not release a specific Covid-19 budget in their expenditures for 2022-23, but we can assume it's on a similar scale as in 2021-22 (in the billions). If we multiply our cost by 10.4 (52 weeks / 5 weeks), we get a cost of around 145 million. Then since we only looked at Montréal (which is around 4.45% of the canadian population)[4], we can multiply it by 20 which brings us to 2.9 billion dollars. This falls directly into the government's budget, hence we can say our solution is logical in a real-world context.

A detailed analysis of the vaccine distribution, found in Appendix C, reveals the crucial roles played by different suppliers and vaccination centers. For instance, "Moderna" was a key supplier to centers like Lachine, Berri-UQAM, and Parc-Extension, whereas "Pfizer-BioNTech" focused on Kirkland, Décarie, and Laval. The distribution was well-orchestrated over a five-week period, ensuring that each week's allocation was adjusted dynamically to meet the changing demands of various centers.

The strategic selection of centers like Montérégie-Centre, Lanaudière, and Laval as major recipients indicates a focus on areas with higher demand, aligning the supply chain with the needs of the population. This strategic approach underlines the model's capability to adapt to and effectively manage varying supply and demand scenarios across different regions.

---

[3] Government of Canada. (November 26th 2021). COVID-19 Planned Expenditures for Supplementary Estimates. https://www.canada.ca/en/treasury-board-secretariat/services/planned-government-spending/supplementary-estimates/supplementary-estimates-b-2021-22/covid-19-planned-expenditures.html
[4] Statistics Canada. (2023). Population And Demography Statistics. https://www.statcan.gc.ca/en/subjects-start/population_and_demography

5.3 Results Interpretation (Sensitivity Analysis)

The sensitivity analysis (view Appendix D for graph) of our COVID-19 vaccine distribution model in Montreal reveals its robustness and responsiveness to varying supply and demand scenarios. It highlights the model's efficiency in handling supply constraints for different vaccines, like the surplus of 173 "Moderna" doses on week 0 and 573 doses on week 3. Similarly, "Novavax" showed an underutilization with a surplus of 605 doses in week 4. This indicates that the supply of certain vaccines occasionally exceeded the demand (view Appendix E for heatmap).

Demand constraints varied across neighborhoods, reflecting the model's geographic focus. For instance, l'Ouest-de-l'Île-de-Montréal almost met its vaccine demand, with a slight unmet demand shown by slack values of 0.65 on week 0 and 1.70 on week 4. In contrast, the Centre-Sud-de-l'Île-de-Montréal experienced more significant unmet demands, particularly on weeks 1 and 2, with slack values of 298.57 and 320.81, respectively, suggesting a larger gap between supply and demand.

Furthermore, adherence to non-negativity constraints ensure realistic and feasible distribution plans. Distributions like 275, 279, and 274 doses of "AstraZeneca" to Kirkland on weeks 0, 3, and 4, respectively, complied with these constraints, indicating effective utilization of available vaccines.

In summary, the analysis underscores the model's capability to navigate complex logistical challenges while striving for equitable and efficient vaccine distribution. It also reveals areas for potential improvement, such as better aligning supply with demand and ensuring uniform distribution across regions.

5.4 Solution Impact

Our solution helps many people, governments, and companies that supply vaccines. It makes getting vaccines faster and easier for people, so they don't have to travel far or wait long. Governments can use their money better and move vaccines quickly to places with more COVID-19 cases. Vaccine companies can send more vaccines to busy hospitals and keep them stored safely.

The model also mirrors the urgency of addressing public health crises, where timely and equitable vaccine distribution is key to mitigating the spread of disease and reducing mortality rates. By prioritizing areas with higher case and death rates, the model aligns with real-world strategies, focusing on hotspots to maximize the impact of intervention measures. This approach is particularly relevant in urban areas where population density and mobility patterns can significantly affect the spread of infectious diseases.

In summary, this model serves as a microcosm of the larger challenges in public health logistics, highlighting the importance of strategic planning, data-driven decision-making, and adaptability in responding to health emergencies.

6. Problem Extensions

6.1 Extension 1: Historical Vaccine Allocation In Urgency

As we aimed to refine our linear optimization model for vaccine distribution, we considered extending its scope to incorporate historical vaccine allocations in the urgency factor. This extension aimed to capture the influence of past vaccine allocations, reflecting their impact on the current unmet demand in high-intensity regions. To do this, we would have added an additional section to our urgency factor. Instead of just having alpha*cases and beta*deaths, we would also include a factor that calculates the cumulative vaccines distributed in all weeks to that area before a certain week. This factor would now be multiplied by gamma (another weighting factor). The new term would calculate xi,j,t-1, where instead of looking at t, we look at the cumulative vaccines delivered at t-1. The new urgency formula would now look like this:

$$\mathbf{u_{nt} = \alpha \cdot Cases_n t + \beta \cdot Deaths_{nt} - \gamma \cdot \sum_{i \in I(n), j} x_{ij,t-1} \quad for\ t>1}$$

The implementation of this dynamic model introduced complexities due to the non-convex nature of the problem. The interdependence of decision variables across different time periods posed challenges in achieving a globally optimal solution. We tried to include this in our code at the beginning but we kept getting error messages through Gurobi. Although we encountered obstacles in coding (view Appendix F for Gurobi output), integrating historical vaccine allocations into the urgency factor could potentially yield a more nuanced evaluation of the vaccination strategy's effectiveness and inform more informed decision-making in current allocation strategies. To sum up, by adding prior allocation's efficacy into the model, we aim to better assess the residual effects on present demand. This refined model intends to equip decision-makers with a more robust tool for strategic planning, enabling them to proactively address the challenges of vaccine distribution and optimize the allocation process more efficiently.

6.2 Extension 2: Adding Government Budget Constraint

In addition, we proposed enhancing the optimization model by incorporating a constraint linked to the government's budget. This addition sets a financial limit on vaccine-related expenditures, closely reflecting real-world fiscal constraints. By imposing this restriction, the model not only optimizes distribution logistics but also ensures financial viability within the allocated resources. If we were to add this constraint, we would have to collect some data (perhaps do some interviews with people working in public health) to see how much budget is specifically allocated to transportation of covid-19 vaccines. We have the total covid-19 budget expenditures, but we don't know the breakdown of where that money is allocated, so this would be an interesting extension.

If we were to add this constraint, it would diminish the feasible area of our solution. If the budget was lower than our optimal solution (13 million), it would be a binding constraint. Hence, the impact of this extension on our model would diminish the number of vaccines we would be able to buy/deliver and decrease our optimal solution.

6.3 Extension 3: Possible: Extending scope to waste management

The incorporation of a waste management constraint into the vaccine distribution model would be very pertinent, particularly in addressing Canada's struggle with excess vaccine wastage. To effectively integrate this constraint, a wastage penalty mechanism can be added to the model. This penalty would signify the cost incurred for proper disposal of unused or expired vaccines. By introducing a financial penalty proportional to the quantity of wasted vaccines, the model actively incentivizes minimizing wastage, aligning with the Public Health Agency of Canada's (PHAC) aim to maintain the national unused vaccine count below 5%[5]. This strategic addition imposes stringent waste management practices within the model, influencing distribution methods and inventory handling to mitigate wastage effectively. Such measures not only align with the PHAC's waste reduction directives but also bolster the efficiency of vaccine deployment strategies by considering the costs associated with vaccine wastage.

6.4 Extension 4: Adding Age Group & Temperature Constraints

The logistical challenges posed by Pfizer and Moderna vaccines, necessitating ultra-cold storage conditions of -70°C and -20°C respectively, demand meticulous planning and infrastructure readiness, constraints that significantly impact their distribution. Hence, it could be an interesting extension to look into vaccine temperatures and how they are sustained during shipments/travel. Furthermore, the age-related safety concerns observed with AstraZeneca and Johnson & Johnson vaccines have prompted regulatory advisories, limiting their usage in specific age groups due to potential rare blood clotting issues. Simultaneously, vaccines like Novavax and Sanofi are undergoing continual evaluation, their efficacy and potential limitations subject to ongoing research. Thus, adapting our model to limit certain vaccines where the population is high-aged and vice-versa would contribute significantly towards formulating distribution plans that not only optimize vaccine allocation but also realistically adhere to the intricate constraints and limitations evident in practical vaccine deployment scenarios.

[5] Aubrey, L., Ishak, A., Dutta, S., Rajesh, E., Suvvari, T. K., & Mukherjee, D. (2022). COVID-19 vaccine wastage in Canada, a reason for concern?. Canadian journal of public health = Revue canadienne de sante publique, 113(2), 209–210. https://doi.org/10.17269/s41997-022-00616-w.

7. Recommendations and Conclusion

7.1 Recommendations

Given the pivotal role of Novavax as a primary supplier, the government should strengthen its relationship with them for future vaccine supplies. Additionally, it may be beneficial to reassess and potentially re-negotiate terms with suppliers like AstraZeneca, given their lesser contribution. Additionally, vaccination centers such as Montérégie-Centre and Lanaudière, which received the largest shares, should be prioritized for resource allocation. The government should consider boosting infrastructure and staffing in these centers to handle the high demand efficiently. As seen in the results section, the model successfully optimized total costs to CAD 13 million. It's crucial to continue this cost-effective approach in future distribution strategies, possibly exploring avenues for further cost reductions without compromising vaccine delivery efficacy. It's essential to meet the demand, particularly for those at risk and more vulnerable to illness.

7.2 Strengths and Weakness of our Process

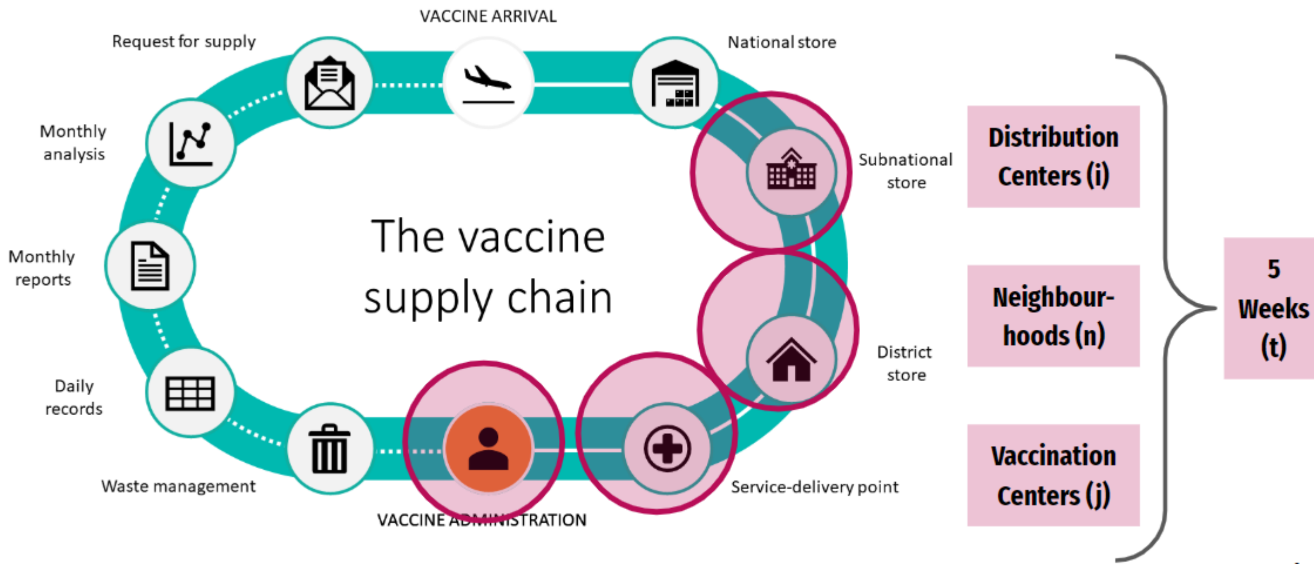
The process showcased strengths in adaptability, with the model flexibly handling diverse data types. Rigorous testing ensured a robust approach, exploring various scenarios and configurations. Effective team communication played a key role, aligning members for a cohesive effort. The model's comprehensiveness, considering factors like supply limits and regional demand variations, enhanced its effectiveness in addressing the complex challenge of vaccine distribution. However, weaknesses arose, particularly in data collection. Challenges in gathering consistent data across timelines and locations impacted accuracy and timeliness. The open-ended nature of the project led to significant time allocated to defining the model, rather than coding and result interpretation. In retrospect, a more focused approach from the outset, with clearer objectives, could have enhanced efficiency, allowing for quicker implementation and refinement of the model.

7.3 What would be done differently

By doing this project, we learned a lot. Data is hard to collect and will not always be clean or as you need it. The model itself was also hard to model for exactly what we wanted, and kept changing during the course of time that we worked on the project. If we were to redo this project, we would spend more time improving data collection methods, particularly through closer collaboration with public health professionals. This would ensure access to more precise and timely data. Additionally, establishing a clear project scope at the beginning would be crucial. This early scoping would streamline efforts, allowing the team to concentrate on critical aspects of the model, thereby saving time and enhancing overall efficiency.

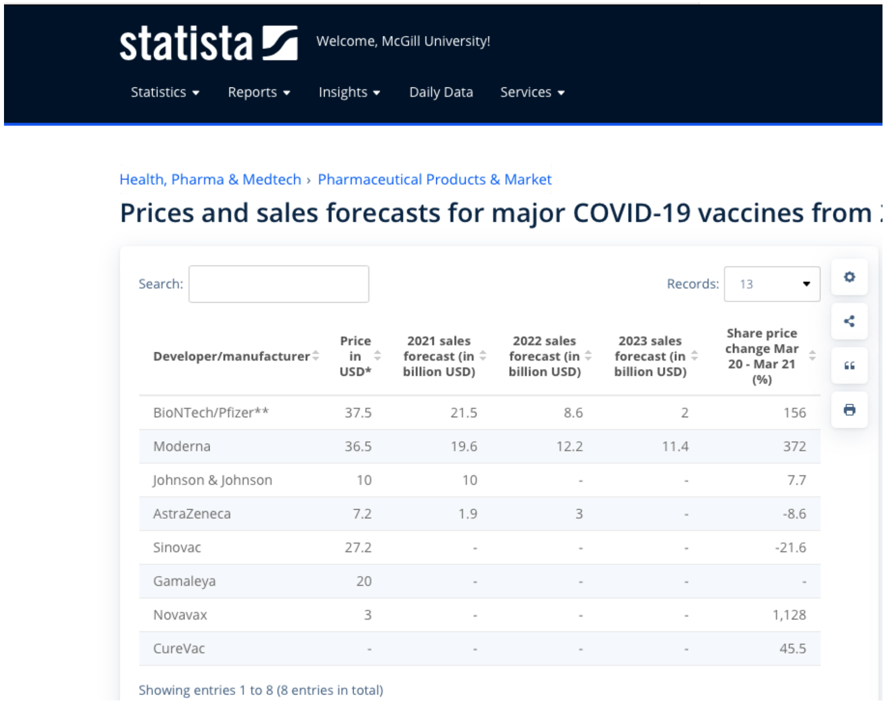
8. Appendices

Appendix A : The Vaccine Supply Chain & Areas of Focus Graph



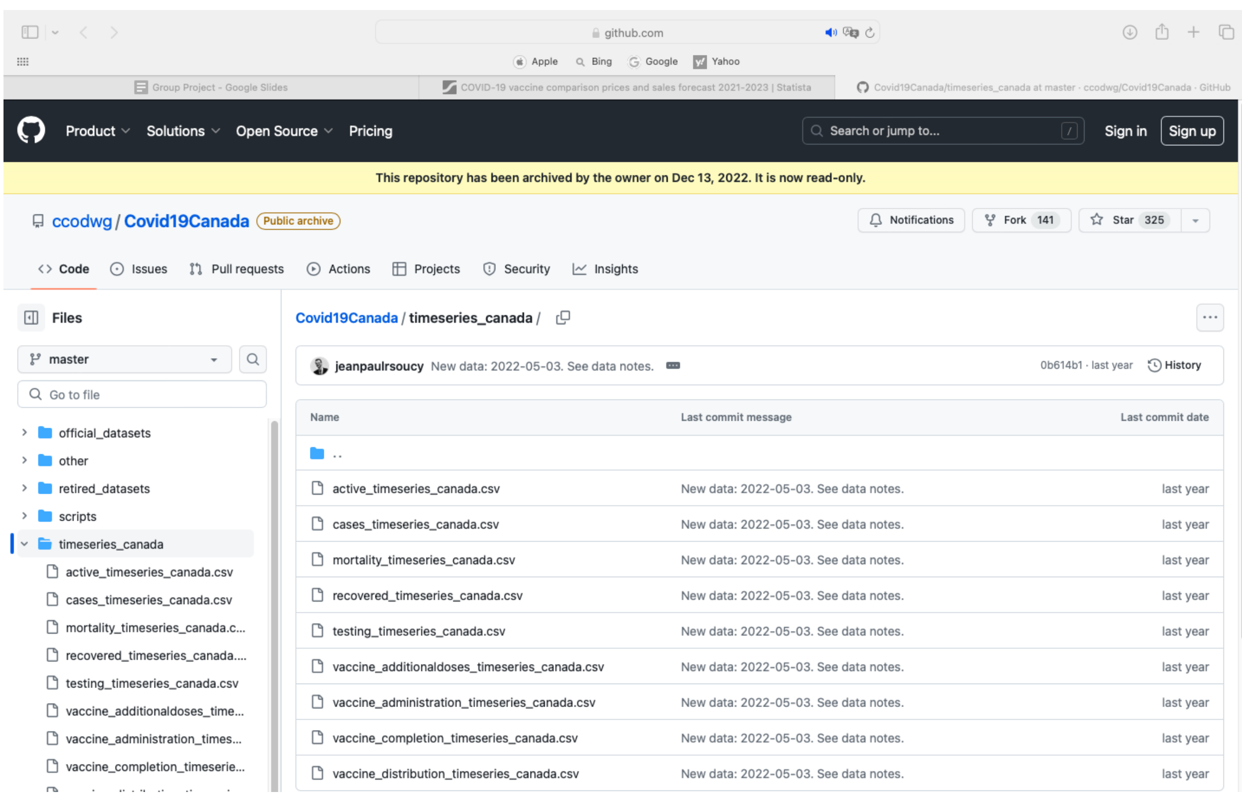
**Left Graph Source:* World Health Organization. (2023). Essential Programme on Immunization. https://www.who.int/teams/immunization-vaccines-and-biologicals/essential-programme-on-immunization/supply-chain

Appendix B : Data Sources Screenshots



Developer/manufacturer	Price in USD*	2021 sales forecast (in billion USD)	2022 sales forecast (in billion USD)	2023 sales forecast (in billion USD)	Share price change Mar 20 - Mar 21 (%)
BioNTech/Pfizer**	37.5	21.5	8.6	2	156
Moderna	36.5	19.6	12.2	11.4	372
Johnson & Johnson	10	10	-	-	7.7
AstraZeneca	7.2	1.9	3	-	-8.6
Sinovac	27.2	-	-	-	-21.6
Gamaleya	20	-	-	-	-
Novavax	3	-	-	-	1,128
CureVac	-	-	-	-	45.5

Showing entries 1 to 8 (8 entries in total)

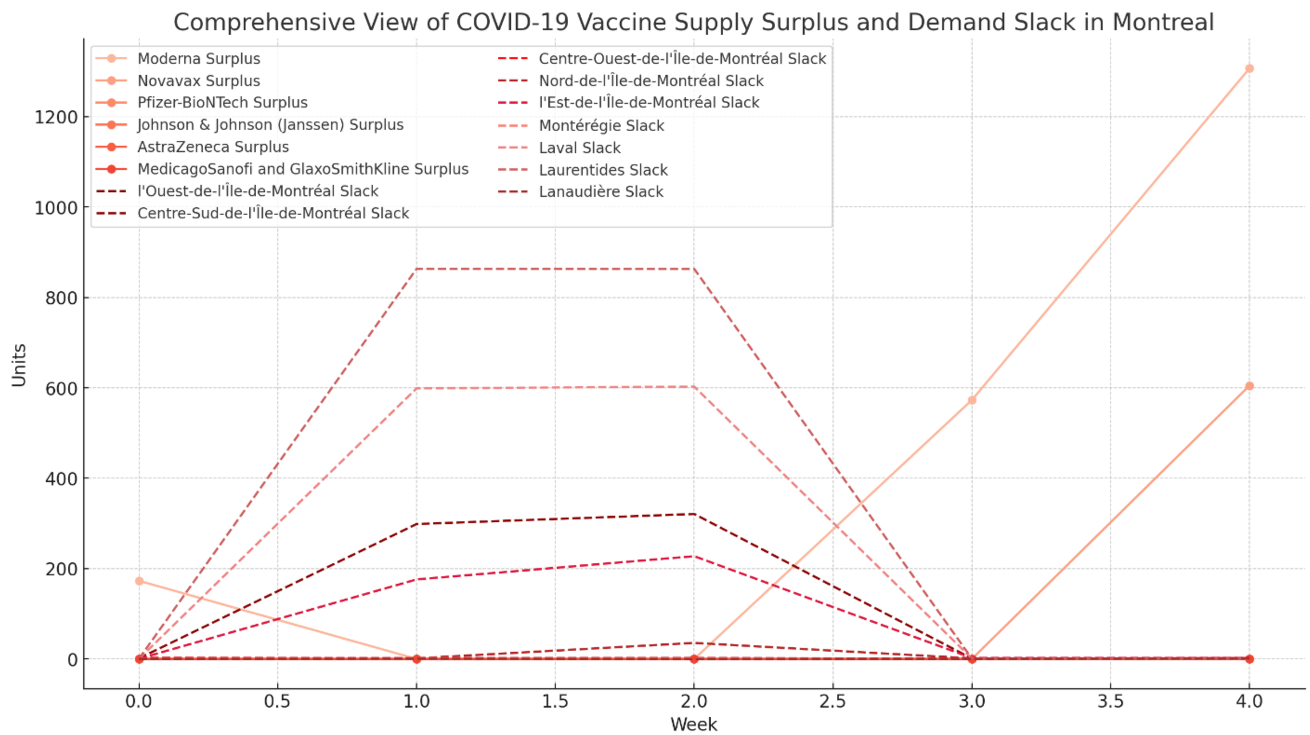


Note: We used the vaccine_distribution_timeseries_canada.csv as dataset for the weekly supply

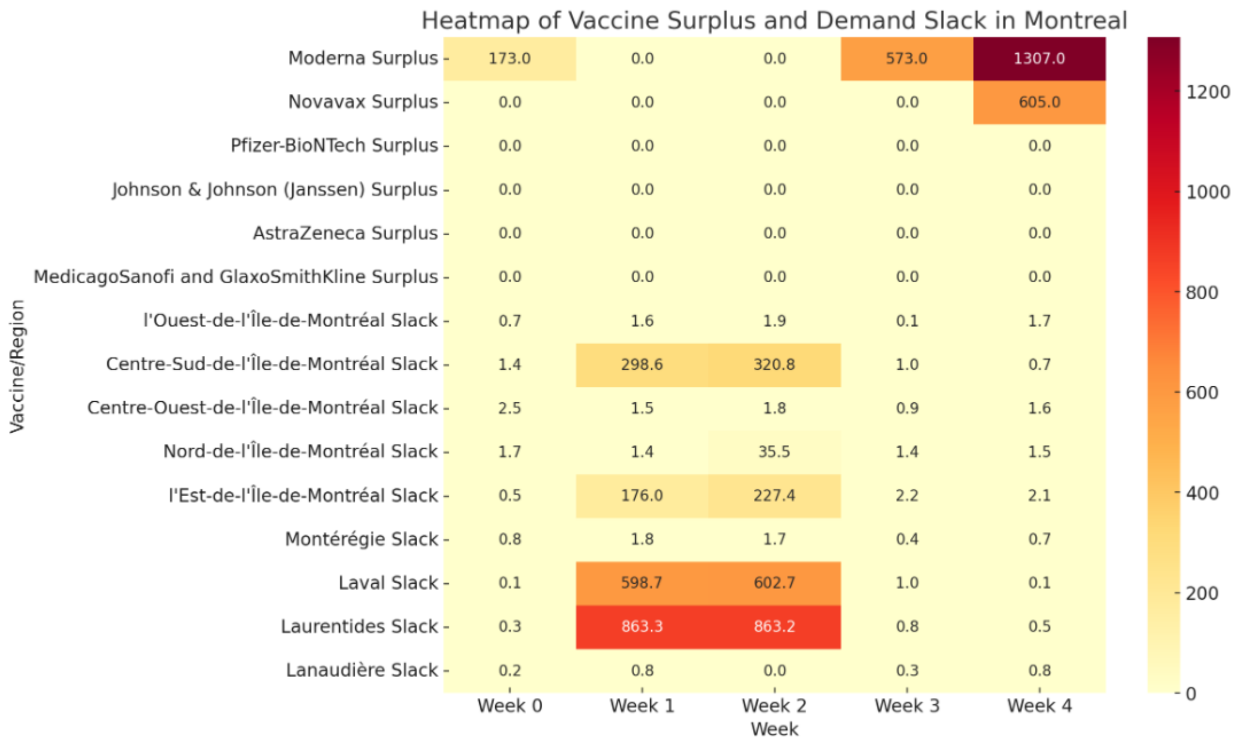
Appendix C : Complete Gurobi Solution Matrix

		Kirkland	Lachine	Berri-UQAM	Verdun	Parc-Extension	Décarie	Saint-Laurent	Montréal-Nord	Chauveau	CLSC Est	Saint-Michel	Montérégie-Centre	Montérégie-Ouest	Laval	Laurentides	Universitaire De Sante	Lanaudière
t=0	Moderna		72	207		181	175	61						182				
	Pfizer-BioNTech						6								665	366	181	
	Johnson & Johnson (Janssen)													907				
	AstraZeneca	275	203															
	Novavax				207							262	750			596		
	Sanofi and GlaxoSmithKline								61	262	262		339					795
t=1	Moderna		274	58	58	180		61						112				
	Pfizer-BioNTech	274				1	181		61						67	96	181	
	Johnson & Johnson (Janssen)													641				
	AstraZeneca													338				
	Novavax											203	1080					
	Sanofi and GlaxoSmithKline									203	203		11					798
t=2	Moderna		274	47		181		44						180				
	Pfizer-BioNTech	274					181		43						67	96	181	
	Johnson & Johnson (Janssen)				47									580				
	AstraZeneca													330				
	Novavax											186	1069					
	Sanofi and GlaxoSmithKline								1	186	186		21					795
t=3	Moderna		50	120		184		62						128				
	Pfizer-BioNTech						184								668	258	184	
	Johnson & Johnson (Janssen)													964				
	AstraZeneca	279	229															
	Novavax				210							265	750			704		
	Sanofi and GlaxoSmithKline			90					62	265	265		342					803
t=4	Moderna																	
	Pfizer-BioNTech					181	181								666	305	181	
	Johnson & Johnson (Janssen)			18				15						1095				
	AstraZeneca	274	274					46										
	Novavax				207							261	527			657		
	Sanofi and GlaxoSmithKline			189					61	261	261		568					798

Appendix D : Sensitivity Analysis Graph for suppliers (i) and neighbourhhods (n) over t (5 weeks)



Appendix E : Sensitivity Analysis Heatmap for suppliers (i) and neighbourhoods (n)



Appendix F : Screenshot of Extension 1 Gurobi Output

```
In [21]:
#urgency_penalty = gp.quicksum(
#    (alpha * cases[n][t] + beta * deaths[n][t]
#    for n in neighbourhood_vacc_centers
#    for t in time_periods
#))

# Urgency penalty from problem extension
urgency_penalty = gp.quicksum(
    (alpha * cases[n][t] + beta * deaths[n][t] - gp.quicksum(X[j, i, t-1] for i in neighbourhood_vacc_centers[n] for j in sup
    * (demand[n][t] - gp.quicksum(X[j, i, t] for i in neighbourhood_vacc_centers[n] for j in suppliers))
    for n in neighbourhood_vacc_centers
    for t in time_periods if t > 1
)

print(urgency_penalty)
# General Unmet demand
penalty_unmet_demand = gp.quicksum(
    (h+urgency_penalty) * (demand[n][t] - gp.quicksum(X[j, i, t] for i in neighbourhood_vacc_centers[n] for j in suppliers))
    for n in neighbourhood_vacc_centers
    for t in time_periods
)
```

```
281928.25301720604 + -549.9085041 <gurobi.Var *Awaiting Model Update*> + -549.9085041 <gurobi.Var *Awaiting Model Update*
> + -549.9085041 <gurobi.Var *Awaiting Model Update*> + -549.9085041 <gurobi.Var *Awaiting Model Update*> + -549.9085041
<gurobi.Var *Awaiting Model Update*> + -549.9085041 <gurobi.Var *Awaiting Model Update*> + -549.9085041 <gurobi.Var *Awai
ting Model Update*> + -549.9085041 <gurobi.Var *Awaiting Model Update*> + -549.9085041 <gurobi.Var *Awaiting Model Update
*> + -549.9085041 <gurobi.Var *Awaiting Model Update*> + -549.9085041 <gurobi.Var *Awaiting Model Update*> + -549.9085041
<gurobi.Var *Awaiting Model Update*> + -2.54 <gurobi.Var *Awaiting Model Update*> + -2.54 <gurobi.Var *Awaiting Model Upd
ate*> + -2.54 <gurobi.Var *Awaiting Model Update*> + -2.54 <gurobi.Var *Awaiting Model Update*> + -2.54 <gurobi.Var *Awai
ting Model Update*> + -2.54 <gurobi.Var *Awaiting Model Update*> + -2.54 <gurobi.Var *Awaiting Model Update*> + -2.54 <gu
robi.Var *Awaiting Model Update*> + -2.54 <gurobi.Var *Awaiting Model Update*> + -2.54 <gurobi.Var *Awaiting Model Update
*> + -2.54 <gurobi.Var *Awaiting Model Update*> + -2.54 <gurobi.Var *Awaiting Model Update*> + -558.1510383 <gurobi.Var *
Awaiting Model Update*> + -558.1510383 <gurobi.Var *Awaiting Model Update*> + -558.1510383 <gurobi.Var *Awaiting Model Up
date*> + -558.1510383 <gurobi.Var *Awaiting Model Update*> + -558.1510383 <gurobi.Var *Awaiting Model Update*> + -558.151
0383 <gurobi.Var *Awaiting Model Update*> + -558.1510383 <gurobi.Var *Awaiting Model Update*> + -558.1510383 <gurobi.Var
*Awaiting Model Update*> + -558.1510383 <gurobi.Var *Awaiting Model Update*> + -558.1510383 <gurobi.Var *Awaiting Model U
pdate*> + -558.1510383 <gurobi.Var *Awaiting Model Update*> + -558.1510383 <gurobi.Var *Awaiting Model Update*> + -2.6700
000000000004 <gurobi.Var *Awaiting Model Update*> + -2.6700000000000004 <gurobi.Var *Awaiting Model Update*> + -2.6700000
000000004 <gurobi.Var *Awaiting Model Update*> + -2.6700000000000004 <gurobi.Var *Awaiting Model Update*> + -2.6700000000
000004 <gurobi.Var *Awaiting Model Update*> + -2.6700000000000004 <gurobi.Var *Awaiting Model Update*> + -2.670000000000
004 <gurobi.Var *Awaiting Model Update*> + -2.6700000000000004 <gurobi.Var *Awaiting Model Update*> + -2.6700000000000004
```

GurobiError: Invalid argument to QuadExpr multiplication

9. References

Aubrey, L., Ishak, A., Dutta, S., Rajesh, E., Suvvari, T. K., & Mukherjee, D. (2022). COVID-19 vaccine wastage in Canada, a reason for concern?. Canadian journal of public health = Revue canadienne de sante publique, 113(2), 209–210. https://doi.org/10.17269/s41997-022-00616-w.

Bernanke, J. (2021, April 9). What's the risk of getting hospitalized with COVID? https://covid-101.org/science/whats-the-risk-of-getting-hospitalized-with-covid/

Centris. (2023). Montréal (Montréal-Nord), Montréal (Île): profil de la population. https://www.centris.ca/fr/outils/profil-de-la-population/montreal-ile/montreal-montreal-nord

CIUSSS de l'Est-de-l'Île-de-Montréal. (2022, July 19). Portrait de la population de l'Est. https://ciusss-estmtl.gouv.qc.ca/propos/connaitre-votre-ciusss/portrait-de-la-population-de-lest

CIUSSS de l'Ouest-de-l'Île-de-Montréal. (2023, November 22). Portrait du CIUSSS. https://www.ciusss-ouestmtl.gouv.qc.ca/notre-ciusss/portrait-du-ciusss/

CIUSSS du Centre-Ouest-de-l'Île-de-Montréal. (2022, June 14). Portrait de la population du CIUSSS. https://www.ciussscentreouest.ca/programmes-et-services/sante-mentale-et-dependance/portrait-de-la-population-du-ciusss/

CIUSSS du Centre-Sud-de-l'Île-de-Montréal. (2019, May 27). Territoire et population desservie. https://ciusss-centresudmtl.gouv.qc.ca/propos/qui-sommes-nous/territoire-et-population-desservie

COVID-19 Data Working Group. (2022, December 13). Weekly vaccine supply coming to Canada. https://github.com/ccodwg/Covid19Canada/tree/master/timeseries_canada

D'Andrea, A. (2023, August 23). Canada 'likely at the start' of new COVID-19 wave. How big will it get? Global News. https://globalnews.ca/news/9914128/canada-covid-fall-wave-2023/

Dickson, S.D., (Sep 02, 2023). More COVID cases are coming. Here's what you need to know. CBC News. https://www.cbc.ca/news/canada/ottawa/more-covid-cases-are-coming-here-s-what-you-need-to-know-1.6951092

Government of Canada. (2023, April 26). Initial supply agreement of each vaccine for Canada. https://www.canada.ca/en/public-services-procurement/services/procuring-vaccines-covid19.html

Government of Canada. (November 26th 2021). COVID-19 Planned Expenditures for Supplementary Estimates (B), 2021-22. https://www.canada.ca/en/treasury-board-secretariat/services/planned-government-spending/supplementary-estimates/supplementary-estimates-b-2021-22/covid-19-planned-expenditures.html

Institut de la statistique du Québec. (2020). Region population estimates. https://statistique.quebec.ca/en/produit/tableau/estimations-population-regions-administratives

Johansen, H., Nguyen, K., Mao, L., Marcoux, R., Gao, R.-N., & Nair, C. (2004). Influenza vaccination. Health Reports, 15 (2), 33-43. Statistics Canada Catalogue 82-003.

Ministère de l'Économie, de l'Innovation et de l'Énergie. (2023, June 14). Démographie. https://www.economie.gouv.qc.ca/pages-regionales/monteregie/portrait-regional/demographie/

Ministère de l'Économie, de l'Innovation et de l'Énergie. (2023, June 15). Démographie. https://www.economie.gouv.qc.ca/pages-regionales/laurentides/portrait-regional/demographie/

Ministère de l'Économie, de l'Innovation et de l'Énergie. (2023, June 20). Démographie. https://www.economie.gouv.qc.ca/pages-regionales/lanaudiere/portrait-regional/demographie/

Pelley, L. (Aug 18, 2023). Early signs suggest fall COVID-19 wave starting in Canada — before updated boosters are available. CBC News. https://www.cbc.ca/news/health/fall-covid-wave-boosters-1.6939751

Public Health Agency of Canada. (2022, August 19). COVID-19 epidemiology update: Current situation. https://health-infobase.canada.ca/covid-19/current-situation.html?stat=num&measure=cases_weekly&map=hr#a2

Public Health Agency of Canada. (2023). Prevalence of Chronic Diseases and Risk Factors among Canadians aged 65 years and older. https://www.canada.ca/en/services/health/publications/diseases-conditions/prevalence-chronic-disease-risk-factors-canadians-aged-65-years-older.html

Public Health Agency of Canada. (2023, January). Seasonal Influenza Vaccination Coverage in Canada, 2021–2022: Full report. https://www.canada.ca/en/public-health/services/immunization-vaccines/vaccination-coverage/seasonal-influenza-survey-results-2021-2022/full-report.html

Statistics Canada. (December 21, 2022). Population estimates on July 1st, by age and sex. https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1710000501

Statistics Canada. (2023). Population And Demography Statistics. https://www.statcan.gc.ca/en/subjects-start/population_and_demography

Statistics Canada. (2023, September 27). Population estimates. https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1710000901

Statista. (March 2021). Prices and sales forecasts for major COVID-19 vaccines from 2021 to 2023. https://www.statista.com/statistics/1221576/covid-vaccines-sales-forecast-mean-price-share-growth/

The Canadian Press. (Sep 09, 2021). Average cost for COVID-19 ICU patients estimated at more than $50,000: report. CBC News. https://www.cbc.ca/news/health/cihi-covid19-canada-hospital-cost-1.6168531

Vlaardingen, C., DePape, K.,. (Aug. 31, 2023.). A new COVID-19 variant is spreading in Quebec—here is the latest guidance. CTV News Montreal. https://montreal.ctvnews.ca/a-new-covid-19-variant-is-spreading-in-quebec-here-is-the-latest-guidance-1.6512937

World Health Organization. (2023). Essential Programme on Immunization. https://www.who.int/teams/immunization-vaccines-and-biologicals/essential-programme-on-immunization/supply-chain

World Population Review. (2023). Laval Population 2023. https://worldpopulationreview.com/canadian-cities/laval-population