engineering proceedings

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Proceeding Paper

Optimizing Strategic Personal Protective Equipment Stockpiling: An Assessment Using Morris Sensitivity Analysis †

Reza Shahin [1,*], Martin Beaulieu [2], Valérie Bélanger [2] and Martin Cousineau [2]

[1] Department of Mathematical and Industrial Engineering, Polytechnique Montréal, Montréal, QC H3T 1J4, Canada
[2] Department of Logistics and Operations Management, HEC Montréal, 3000 Chemin de la Côte Sainte-Catherine, Montréal, QC H3T 2A7, Canada; martin.beaulieu@hec.ca (M.B.); valerie.3.belanger@hec.ca (V.B.); martin.cousineau@hec.ca (M.C.)
* Correspondence: rezaa.shahin.1992@gmail.com

† Presented at the 1st International Conference on Industrial, Manufacturing, and Process Engineering (ICIMP-2024), Regina, Canada, 27–29 June 2024.

Abstract: This paper analyzes healthcare supply chain shortcomings during the COVID-19 pandemic, specifically in supplying personal protective equipment (PPE) to healthcare personnel. It addresses the need for effective PPE stockpile strategies, considering past inadequacies. A linear programming model is presented to determine optimal PPE stockpile levels, factoring in unpredictable demand and variable supplier costs. The study includes a comparative analysis of scenarios with and without stockpiling strategies. Moreover, we employ the Morris method for comprehensive sensitivity analysis, focusing on key factors, namely: demand, supply from traditional and non-traditional sources, and stockpile capacity. These insights are vital for policymakers to develop better PPE stockpiling methods, thus improving healthcare crisis management.

Keywords: personal protective equipment; stockpiling; sensitivity analysis; linear programming; optimization; mathematical modeling; Morris method

Citation: Shahin, R.; Beaulieu, M.; Bélanger, V.; Cousineau, M. Optimizing Strategic Personal Protective Equipment Stockpiling: An Assessment Using Morris Sensitivity Analysis. *Eng. Proc.* **2024**, *76*, 29. https://doi.org/10.3390/engproc2024076029

Academic Editors: Golam Kabir, Sharfuddin Khan, Mohammad Khondoker and Hussameldin Ibrahim

Published: 21 October 2024

1. Introduction

The COVID-19 pandemic highlighted significant weaknesses in the healthcare supply chain, particularly in personal protective equipment (PPE) distribution within hospitals [1]. Unlike other sectors, hospitals cannot cease operations during crises, making reliable PPE supply crucial. Despite efforts by several countries to establish PPE reserves, these measures often fell short during emergencies, as evidenced during the early stages of the COVID-19 pandemic when the United States experienced a severe PPE shortage. Healthcare personnel have urged governments to ensure sufficient PPE supplies, including gloves, medical masks, spectacles or face shields, garments, and N95 respirators. N95 respirators, critical for reducing respiratory infections, were in short supply, increasing the risk of healthcare personnel transmitting the virus to patients.

The stability of the healthcare system was jeopardized by a simultaneous decrease in supply, due to an increase in demand for care, leading to diminished quality and quantity of available care. This situation not only exacerbated the demand for treatment but also reduced the healthcare system's capacity. The scarcity of PPE evolved from being an occupational health issue to a systemic public health concern. PPE is crucial for infection prevention and control among healthcare personnel, whose protection is vital for effective pandemic containment. The COVID-19 pandemic significantly escalated global demand for medical products, causing substantial disruptions and severe shortages in supplies. In response, the World Health Organization (WHO) called for a 40% increase in production in March 2020 to meet this surge. Public health government organizations (PHGOs) face the challenge of ensuring reliable access to PPE, including face masks, gloves, gowns, and eye protection, to effectively manage pandemics. This task is complicated by the unpredictable nature and duration of pandemics. During COVID-19, PHGOs struggled to maintain a stable PPE supply, as evidenced by reported shortages of ventilators and PPE in the United States and across various European countries, including the UK and France. Strategic PPE stocks held by PHGOs were inadequate, leading to intense global competition for procurement from manufacturers, further strained by supply chain disruptions caused by the pandemic.

In response to pandemics and epidemics, stockpiling PPE has been a common strategy, as evidenced by Ontario actions post-SARS, accumulating millions of face masks. However, challenges such as funding constraints often lead to issues like expired products, a problem not unique to Ontario but seen globally, including in the US, UK, and France [1]. Effective management of PPE stockpiles is crucial throughout the stages of a pandemic, requiring policymakers to accurately determine the optimal PPE quantity to handle unpredictable demand and supply dynamics. This strategic planning is vital, especially when pandemics disrupt supply chains, leading to potential shortages and exacerbating outbreaks. This study addresses the research gap in evaluating stockpiling strategies' effectiveness on healthcare outcomes and supply chain resilience during pandemics. While existing literature often emphasizes the immediate benefits of stockpiling, there is a lack of empirical evidence on its tangible impact. Our research aims to quantify the contribution of stockpiling to supply chain robustness and healthcare preparedness, enhancing the understanding of stockpiling as a strategic pandemic response.

This study addresses three critical questions: (1) the effect of stockpiling on reducing overall supply chain costs, (2) the efficacy of stockpiling in minimizing missed demands compared to a non-stockpiling scenario, and (3) the identification of the most influential parameter(s) among level of demand, production capacity of traditional and non-traditional suppliers, as well as stockpile capacity. To explore these, a linear programming (LP) formulation is proposed, incorporating uncertainties in demand and supply of both supplier types and aimed at identifying suitable stockpile levels. The model is evaluated through sensitivity analysis, examining how changes in input parameters, namely, level of demand, production capacity of traditional and non-traditional suppliers, and stockpile capacity, impact results. Due to the complex nature of sensitivity analysis, the study emphasizes the importance of a design of experiments (DoE) approach for efficient assessment of parameter impacts. This methodology is crucial for effective and efficient pandemic response, particularly in managing PPE resources [2,3].

The commonly used one-factor-at-a-time (OFAT) method in sensitivity analysis, which varies one parameter at a time, is limited in understanding complex parameter interactions and system complexities. In contrast, our study employs the Morris method for global sensitivity analysis, simultaneously varying multiple parameters across their range [4]. This approach is more suitable for complex systems like LP models in contexts such as PPE supply chain management during pandemics. Our research presents an LP model to ascertain optimal PPE stockpiling levels under various scenarios, including those with and without stockpiling. The Morris method allows for a detailed sensitivity analysis, examining how system responses change with variations in demand, production capacity of traditional and non-traditional suppliers, and stockpile capacity. This comprehensive analysis offers valuable insights for effective PPE stockpile management.

The paper is structured as follows: literature review in Section 2, problem description and mathematical model in Section 3, methodology in Section 4, results in Section 5, and conclusions and future research directions in Section 6.

2. Literature Review

In this section, we conduct an exhaustive analysis of papers pertinent to the optimization problem under consideration. A comprehensive examination of the relevant literature is conducted, culminating in a detailed synopsis at the end of this section. Special attention is given to the aspects of sensitivity analysis within these studies, where relevant.

The study in [5] presented a game theory model for PPE stock management in healthcare facilities, employing a decentralized approach with centralized oversight on pricing and supply. It shows that strategic stockpiling and enhanced storage significantly reduce PPE costs, with the impact varying with the timing of a potential second COVID-19 wave. This approach improves cost efficiency and supply chain stability, highlighting its effectiveness in pandemic scenarios. In [6], a resilience-focused framework for PPE supply chains was introduced, utilizing a multi-period, multi-objective optimization model for a Canadian healthcare setting. It underlines the critical role of emergency stockpiles and early warning systems in disruption management and informed procurement under uncertainty. In [7], the authors detailed the first empirical investigation into US PPE stockpiles, analyzing types, quantities, and storage conditions based on collaboration with the PPE community and site observations. The findings from examining 20 stockpiles with approximately 53 million respirators offer vital insights into standard storage conditions, contributing to the development of PPE performance assessment protocols over extended storage periods.

The authors in [1] innovatively incorporated fuzzy parameters into linear programming to tackle the inventory routing problem under the supply and demand uncertainties of PPE during the pandemic. They aimed to optimize PPE distribution and inventory planning to minimize costs while preventing wastage or shortages. The study's sensitivity analysis highlighted how the number of PPE distribution centers (DCs), vehicles, and the planning period duration impacts total costs, with more DCs, vehicles, or longer periods leading to higher costs. Key findings suggested the efficiency of minimizing vehicles and clusters to meet demands effectively. In contrast, another study [8] developed a multi-objective, multi-period, and multi-product model for PPE supply chain management during pandemics. They used mathematical modeling and meta-heuristic algorithms to minimize total cost and PPE shortages. The sensitivity analysis showed that increasing storage and production capacities affects total costs and supply chain objectives, while factors like medical center treatment capacity and regional population size increase supply chain costs and demand shortages. Finally, the authors in [9] developed a theoretical model using a Stackelberg game framework to guide governments in PPE management during pandemics. They examined strategies involving PPE stockpiling, subsidies for local production, and spot market purchases to ensure reliable, cost-effective PPE access. The model suggested that a combined strategy of stockpiling, subsidizing local production, and spot market utilization can effectively manage PPE supply in pandemic situations.

Table 1 shows the criteria employed in sensitivity analyses as documented in the existing literature. An examination of the research reveals that the predominant approach to conducting sensitivity analyses has been the OFAT method, notwithstanding the extensive array of criteria explored. In light of this, our research advocates the execution of sensitivity analysis on four principal parameters as shown in the table. To streamline computational efficiency, we adopt the Morris method, which leverages the principles of DoE for input variables. This approach enables a comprehensive assessment of each criterion influence and is designed to explore interactions between input factors and their non-linear effects on the output. This is a significant advantage over the OFAT approach, which, by altering one factor at a time, fails to capture the complex interactions [4].

Table 1. Summary of sensitivity analysis in the literature; C1: number of PPE distribution centers; C2: number of vehicles; C3: number of time periods; C4: stockpile capacity; C5: distributor capacity; C6: production capacity of traditional supplier; C7: transportation cost; C8: job opportunity weight; C9: emissions; C10: level of demand; C11: production capacity of non-traditional supplier.

References	Criteria											Method
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	
[1]	x	x	x									OFAT
[3]				x	x	x						OFAT
[8]				x	x		x	x	x			OFAT
Current study				x		x				x	x	Morris

3. Problem Description and Mathematical Modeling

In the system under consideration, we consider a stockpile that is designed to store PPE received from suppliers. The supply side is represented by two distinct categories of suppliers: (1) *traditional supplier*: these entities are directly connected to the demand side and primarily serve to fulfill immediate requirements for PPE. In instances where traditional suppliers have excess production that surpasses current demand, the surplus PPE units are directed towards a centralized stockpile; (2) *non-traditional supplier*: these providers are capable of delivering the necessary items, albeit at a marginally higher expense relative to traditional suppliers. The underlying rationale for this cost disparity is attributed to the fact that the non-traditional suppliers primarily focus on different product lines; however, in response to the crisis, they commenced the production of PPE as a measure to mitigate the scarcity issue. In cases where both traditional and non-traditional suppliers as well as stockpile storage are unable to meet the demand, a shortage situation arises. This represents a failure of the system to fulfill the demand for PPE and is considered an undesirable outcome. The objective of this study is to measure how integrating stockpiling strategy in such a system can reduce the overall cost of the supply chain when considering various supply and demand scenarios.

We delineate the mathematical formulation of our proposed LP formulation aimed at integrating the stockpiling strategy of PPE. We consider $T = \{1, 2, \ldots, \overline{T}\}$ to be a set of time periods. Turn our focus to parameters, d_t is the demand at the end of time period t. We let $Q_{W,t}$ and $Q_{Z,t}$ to be the maximum production capacity at the end of time period t by traditional and non-traditional suppliers, respectively. We define the maximum capacity of stockpile to be Q_I. We let w_1, w_2, w_3, and w_4 to be weights for different components of the objective functions. Turning our focus to decision variables, we define I_t as the stockpile level at the end of time period t. We let S_t to be amount of shortage at the end of time period t, while the amount of order at the end of time period t from traditional and non-traditional suppliers are defined as W_t and Z_t, respectively. Having defined the notations, in the following, we provide the model:

$$min w_1 \sum_{t \in T} I_t + w_2 \sum_{t \in T} S_t + w_3 \sum_{t \in T} W_t + w_4 \sum_{t \in T} Z_t \tag{1}$$

Subject to:

$$I_t = W_{t-1} + Z_{t-1} - d_t + I_{t-1} + S_t \forall t \in T \tag{2}$$

$$Z_t \leq Q_{Z,t} \quad \forall t \in T \tag{3}$$

$$W_t \leq Q_{W,t} \quad \forall t \in T \tag{4}$$

$$\sum_{t \in T} I_t \leq Q_I \tag{5}$$

$$W_0, Z_0 = 0 \tag{6}$$

$$I_0 = Q_I \tag{7}$$

$$I_t, Z_t, W_t, S_t \geq 0, \forall t \in T \tag{8}$$

The objective function of the model (1) consists of four components. The first component minimizes the stockpile cost, while the second component minimizes the shortage cost. Components three and four minimize the ordering costs from traditional and non-traditional suppliers, respectively. Constraints (2) compute the level of the stockpile at the end of each time period. Constraints (3)–(4) are the upper bounds on the maximum level of order that non-traditional and traditional suppliers can provide. Constraint (5) provides an upper bound on the stockpile level capacity. Constraints (6) set the production from traditional and non-traditional suppliers to zero, respectively, while Constraints (7) set the initial stockpile level to the size of the stockpile. Finally, Constraints (8) are non-negativity constraints.

4. Methodology

This section is split into two parts. The first tests the model with and without a stockpiling strategy in different scenarios to assess its impact on reducing missed demand and supply chain costs. The second part conducts an extensive Morris sensitivity analysis on four parameters. Previous studies have mainly used the OFAT method for single parameter impact analyses (as noted in Section 1), but this paper explores the effects of multiple parameters using the Morris method. The Morris sensitivity analysis, a global sensitivity technique detailed in [4], aims to determine the effect of input variations on model output by calculating *elementary effects* (EE) for each input setting.

Now we turn our focus to parameters we would like to perform a sensitivity analysis over. We choose to have demand and supply uncertainties, making it possible to understand the behavior of our model in the event of a crisis. For this reason, we perform sensitivity analysis over the level of demand, and production capacity of traditional and non-traditional suppliers, as well as the stockpile capacity. The study focuses on four key parameters pivotal to supply chain responsiveness during a pandemic: (1) the sensitivity of the supply chain to demand fluctuations, ensuring supply adequacy; (2) the ability of traditional suppliers to rapidly increase production in response to demand surges, reflecting supply chain resilience; (3) the contribution of non-traditional suppliers as alternative PPE sources during crises, highlighting innovation potential; and (4) the role of government or health system stockpiles as buffers against shortages, emphasizing the importance of initial levels and stockpile management in early crisis mitigation. This analysis aims to understand the supply-demand dynamics in crisis situations, drawing lessons from the COVID-19 pandemic to enhance future supply chain preparedness and adaptability. We consider d_t to range from 5000 to 30,000, while $Q_{W,t}$ and Q_I range between 5000 and 10,000. $Q_{Z,t}$ ranges between 2500 and 5000. We choose this setting as we would like to investigate the saturation level in which there are plenty of demand to be served, while not enough products are received from suppliers. In this case, we can analyze the optimal value for the PPE stockpile, showing that it can be very much helpful in the case of a crisis. Also, the costs associated with objective function weighs of traditional supplier, non-traditional supplier, stockpile, and missed demand are 0.7, 0.9, 0.75, and 10, respectively.

5. Results

The study divides its findings into two parts: the effectiveness of stockpiling strategies in crisis mitigation and a Morris sensitivity analysis of four pivotal parameters. Preliminary findings from 200 configurations in Figures 1 and 2 reveal the role of stockpiling in diminishing unmet demand, a critical observation during the COVID-19 PPE crisis. The model, explained in Section 3, significantly reduces objective function values and unmet demands by utilizing stockpiles (depicted in blue) instead of relying solely on both suppliers, as showcased in Figure 1. Despite the reduction, Figure 2 highlights residual unmet demands, albeit considerably fewer compared to scenarios without stockpiling—reducing missed demands from around 22,000 units to about 2000 units in certain cases. Yet, the persistence of unmet demands in some scenarios suggests the necessity for accurately determining optimal stockpile sizes. The study underscores the criticality of unlimited stockpile inventories for effective crisis management, recommending that optimal stockpile sizes be derived by accounting for the surplus needed beyond the capacity of traditional suppliers to meet demand surges, with the main hurdle being the accurate prediction of future demand, as discussed in the study's conclusions.

Then, we applied the Morris method, as shown in Table 2, to assess sensitivity using key parameters: mean (μ), absolute mean (μ^*), standard deviation (σ), and confidence interval half-width (μ^*-conf). The mean (μ) reflects the average output change from altering one parameter, with high values indicating significant effects. Positive means suggest positive correlations, while negative ones imply inverse relationships. The absolute mean (μ^*) averages absolute output changes, showing the overall impact of parameter changes on the output, where higher values indicate more significant fluctuations. The standard deviation (σ) measures output variability due to parameter changes. A high standard deviation denotes less predictability in output response, while a low standard deviation suggests more consistent changes. The confidence interval half-width (μ*-conf) indicates the half-width of range for the true value of μ* with a specific confidence level, with narrower intervals signifying more precise estimates.

Figure 1. The objective function values for two strategies.

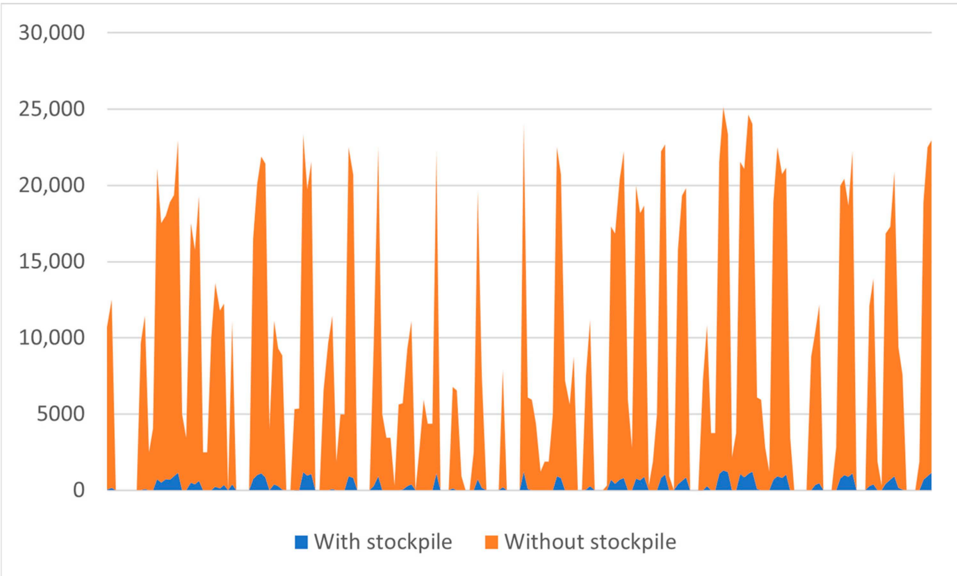

Figure 2. The total number of missed demands for two strategies.

Table 2. Sensitivity analysis results.

Key Parameters	Notation	μ	μ*	σ	μ*-conf
Demand level	d_t	11,392.8	11,392.8	10,890.6	6307.9
Traditional supplier production capacity	$Q_{W,t}$	−4751.8	8479.6	15,385.6	7783.7
Non-traditional supplier production capacity	$Q_{Z,t}$	61.5	16,533	25,615	1046.2
Stockpile capacity	Q_I	9490.3	10,937.8	17,495	10,530.6

Moving to the results, they collectively demonstrate a nuanced interplay of influence and variability across different parameters of the model. Expanding on the initial analysis, the Morris method results present a nuanced understanding of how each parameter influences the model. The non-traditional supplier capacity stands out due to its markedly high absolute mean (μ^*) of 16,533 and an exceptionally high standard deviation (σ) of 25,615. This combination of metrics indicates that the non-traditional supplier capacity not only significantly alters the model output but also contributes to a high degree of uncertainty or variability in the results. The high μ^* value suggests that the effect of it is not just linear but possibly non-linear or involves complex interactions with other parameters. Furthermore, the substantial standard deviation points towards a diverse range of outcomes stemming from changes in this parameter, highlighting its critical role in the model's overall sensitivity and response.

In contrast, the traditional supplier capacity and stockpile capacity also demonstrate considerable influence, as evidenced by their significant μ^* values of 8479.6 and 10,937.8, respectively. However, their impacts are characterized by less variability compared to the non-traditional supplier capacity, as indicated by their lower standard deviations (15,385.6 for the traditional supplier capacity and 17,495 for the stockpile capacity). This suggests that while these parameters substantially affect the model output, the ranges of their impacts are somewhat more predictable or constrained than that of the non-traditional supplier capacity. Additionally, the level of demand, with a mean (μ) of 11,392.8 and a relatively lower standard deviation of 10,890.6, implies a significant but more uniform influence on the model. Its high mean indicates a notable average effect on the output, yet the lower standard deviation compared to other parameters suggests that the variability it introduces is less pronounced, leading to more consistent outcomes.

Overall, these insights underscore the importance of considering both the magnitude and variability of parameter impacts in sensitivity analyses. While the non-traditional supplier capacity is identified as the most influential in terms of both effect and variability, the roles of the traditional supplier capacity, stockpile capacity, and level of demand are also significant, albeit with differing degrees of predictability in their impacts. This comprehensive understanding is vital for informed decision making in model adjustments and prioritizing areas for further investigations. The significant contribution of non-traditional suppliers demonstrates that decision-makers ought to regard them as a viable option to mitigate crises, instead of solely depending on traditional suppliers.

6. Conclusions

In our study, we developed an LP formulation to incorporate a stockpiling strategy for PPE. We tested the model under 200 scenarios using the DoE methodology for performing sensitivity analyses and with and without the stockpiling strategy. The results demonstrated the effectiveness of the stockpiling strategy in reducing unmet demands and total service costs. A sensitivity analysis was conducted on four key parameters (demand level, production capacity of traditional and non-traditional suppliers, and stockpile capacity) using the Morris sensitivity analysis technique, which offers deeper insights than the OFAT method, providing partial insights on model behaviors [10]. The analysis identified the non-traditional supplier capacity as the most influential parameter, significantly impacting the model output. Moreover, there is a notable scarcity in the optimization literature of systematic literature reviews that categorize research papers by their varied problem-solving approaches, akin to the methodology used in [11], but for the COVID-19 field of study. This type of review is crucial for highlighting the development of problems over an estimated five-year span, a facet that remains insufficiently explored. Our study reveals that the methodologies and findings regarding PPE stockpiling for pandemic preparedness hold broader applicability across different supply chain challenges and crisis management scenarios. The strength of our LP approach and the detailed scenario analysis via the DoE technique reinforce the potential extension of our conclusions beyond the immediate context. Although our results are directly relevant to PPE stockpiling, they indicate that similar strategies could be effective in mitigating supply chain disruptions in various sectors.

In terms of limitations, this study does not account for the time required for non-traditional suppliers (two to four weeks) and traditional suppliers (12 weeks) to adjust production in response to increased demand. Including these adjustment periods could lead to more representative results.

This study underscores the crucial role of strategic stockpiling in mitigating supply crisis impacts, showing that missed demands can decrease by around 90% in some scenarios. It is suggested that: (1) governments and organizations invest in robust stockpile management, and decision-makers enhance supply chain resilience; (2) additional research studies policies to establish strategic stockpiles and develop resilient networks; (3) healthcare organizations adopt advanced forecasting models and collaborate with governments for funding.

Author Contributions: R.S., literature review, mathematical modeling, analysis, writing; M.B., conceptualization, validation; V.B., conceptualization, validation; M.C., conceptualization, validation. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used in this study is publicly accessible in the following link: https://drive.google.com/drive/folders/1EsU_pQ-VQjQyX6oLSNkX9r8pQEB3LZQ0?usp=sharing.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Göçmen, E. Linear programming with fuzzy parameters for inventory routing problem in effective management of personal protective equipment: A case study of corona virus disease 2019. *Energy Sources Part A Recovery Util. Environ. Eff.* **2022**, *44*, 9217–9231. [CrossRef]
2. Beaulieu, M.; Roy, J.; Snowdon, A.; Ruel, S. Les pièges à éviter avant la prochaine pandémie. *Gest. Hosp.* **2021**, *603*, 70–71.
3. Scala, B.; Lindsay, C.F. Supply chain resilience during pandemic disruption: Evidence from healthcare. *Supply Chain Manag. Int. J.* **2021**, *26*, 672–688. [CrossRef]
4. Wang, C.; Peng, M.; Xia, G. Sensitivity analysis based on Morris method of passive system performance under ocean conditions. *Ann. Nucl. Energy* **2020**, *137*, 107067. [CrossRef]
5. Abedrabboh, K.; Pilz, M.; Al-Fagih, Z.; Al-Fagih, O.S.; Nebel, J.C.; Al-Fagih, L. Game theory to enhance stock management of Personal Protective Equipment (PPE) during the COVID-19 outbreak. *PLoS ONE* **2021**, *16*, e0246110. [CrossRef] [PubMed]
6. Ash, C.; Diallo, C.; Venkatadri, U.; VanBerkel, P. Distributionally robust optimization of a Canadian healthcare supply chain to enhance resilience during the COVID-19 pandemic. *Comput. Ind. Eng.* **2022**, *168*, 108051. [CrossRef] [PubMed]
7. Greenawald, L.A.; Moore, S.M.; Wizner, K.; Yorio, P.L. Developing a methodology to collect empirical data that informs policy and practices for stockpiling personal protective equipment. *Am. J. Infect. Control* **2021**, *49*, 166–173. [CrossRef] [PubMed]
8. Mosallanezhad, B.; Chouhan, V.K.; Paydar, M.M.; Hajiaghaei-Keshteli, M. Disaster relief supply chain design for personal protection equipment during the COVID-19 pandemic. *Appl. Soft Comput.* **2021**, *112*, 107809. [CrossRef] [PubMed]
9. Hammami, R.; Salman, S.; Khouja, M.; Nouira, I.; Alaswad, S. Government strategies to secure the supply of medical products in pandemic times. *Eur. J. Oper. Res.* **2023**, *306*, 1364–1387. [CrossRef]
10. Shahin, R.; Hosteins, P.; Pellegrini, P.; Vandanjon, P.O. A full factorial sensitivity analysis for a capacitated Flex-Route Transit system. In Proceedings of the 2023 8th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), Nice, France, 14–16 June 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 1–6.
11. Shahin, R.; Hosteins, P.; Pellegrini, P.; Vandanjon, P.O.; Quadrifoglio, L. A survey of Flex-Route Transit problem and its link with Vehicle Routing Problem. *Transp. Res. Part C Emerg. Technol.* **2024**, *158*, 104437. [CrossRef]