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EQUITABLE ALLOCATION OF SCARCE RESOURCES DURING THE COVID-19 PANDEMIC: A CASE STUDY FOR CONVALESCENT PLASMA DISTRIBUTION

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ABSTRACT

Resource planning during pandemics presents many challenges and equitable decisions about resource allocation must be made. There is no standard definition of equity. Robust mathematical formulations can require a lot of data. In a novel pandemic there is limited historical information available to inform decisions. Decision makers can look to define equity through population proportions (pro-rata). This notion of equity is readily implementable. We present a practical framework for an equitable allocation of scarce resources using population proportions, disease demographics, and resource utilization. We assess our framework using a stochastic simulation model, calibrated to COVID-19 case data, in a case study for convalescent plasma distribution in the context of the clinical trial CONCOR-1. We show that pro-rata resource allocation can be inequitable and that decision makers can consider readily available information, such as resource utilization and case data, to inform equity and proactively manage scarce resources during a pandemic.

1 INTRODUCTION

Equity is a notion of fairness or justice, which has no standard definition. Resource planning can be difficult and resource planning during pandemics present unique challenges since resources are often scarce. Equitable decisions about the allocation of resources must be made. Allocating resources to obtain the maximum utility (benefit) is *utilitarianism* (Bertsimas et al. 2011). *Horizontal equity* (Epstein et al. 2007) is the notion that groups in the same circumstances should have similar access to resources. *Vertical equity* (Breugem and Van Wassenhove 2022) is a notion that groups in different circumstances should have different access to resources. *Proportional equity* (Bertsimas et al. 2011) involves distributing resources to a group in proportion to a claim about each group member's worth. *Max-min (Min-max) equity* (Bertsimas et al. 2011) will find an allocation of resources to a group such that trying to increase (decrease) the utility

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of any group member results in a decrease (increase) in the utility among group members with an equal or lesser (greater) utility.

In a novel pandemic there is limited historical information available to inform decisions. Decision makers can look to population and disease demographics to inform an equitable allocation of healthcare resources. In this paper, we present a practical and readily implementable framework to equitably distribute scarce resources based on population proportions, disease demographics, and resource utilization. These strategies subsume aspects of proportional and vertical equity. We assess our framework using a simulation model in a case study for COVID-19 convalescent plasma (CCP) distribution. This paper is organized as follows. Section 2 and Section 3 discuss relevant literature and CONCOR-1, respectively. In Section 4, we present our practical framework for an equitable allocation of resources during a pandemic. We present our model and results in Section 5. We end with a discussion.

2 RELEVANT LITERATURE

There are many factors that go into decision making for the allocation of healthcare resources (Guindo et al. 2012; Lane et al. 2017). In this section we discuss some modelling methodologies oriented towards an equitable distribution of resources. Cost-utility analysis (CUA) (Brandeau et al. 2003), sometimes called cost-effectiveness analysis, has been used to allocate a fixed budget to a set of healthcare interventions that maximizes total utility (sum of health benefits for patients). The optimal solution to this problem is an allocation of funding such that no greater total health benefits can be obtained for the given budget constraint. This is utilitarianism, which has its biases. There is no standard method to determine the utility of each intervention. Assuming a linear and/or deterministic relationship between cost and equity may not always be appropriate. Epstein et al. (2007) incorporate equity concerns, including horizontal equity, as constraints into a CUA formulation and find that imposing their notions of equity results in an optimal resource allocation with utility less than the utility of an optimal allocation from their formulation without equity constraints. Breugem and Van Wassenhove (2022) derive an analytical upper bound for the loss of utility under vertical equity considerations posed as constraints in their mathematical formulation.

Plans-Rubió (2012) studied two priority-setting frameworks for allocating resources to two healthcare interventions based on cost-utility and social-welfare objectives. Argyris et al. (2022) achieve an equitable distribution of resources by maximizing resource allocation efficiency subject to welfare-based dominance constraints. Mathematical models have been used to study equitable resource allocation decisions for HIV prevention activities (Cleary et al. 2010; Earnshaw et al. 2007) and kidneys (Bertsimas et al. 2013; Yuan et al. 1994; Zenios et al. 2000). Bertsimas et al. (2011) compare the relative merit of proportional and max-min equity. The aforementioned models and frameworks may not be readily implementable during a pandemic since they may require data that is not available during a public health emergency, such as the real-time supply and demand for a given resource.

Simulation models (Abdel-Hadi and Clancy 2014; Cao and Huang 2012) have been used to evaluate resource allocation strategies, which is appropriate given the complexity of incorporating equity into a mathematical formulation. Performance measures can vary depending on the underlying notion of equity. Common performance measures for simulation models are costs, utility, waiting times, and quantity of resources allocated. However, it is unclear on how to best use simulation results to inform real-world decision making (Brandeau et al. 2009).

Wu et al. (2007) use a deterministic model to evaluate pre-pandemic influenza vaccine allocation policies, and show that resource allocation based solely on population proportions (pro-rata) may not be the most efficient or equitable. Pro-rata resource allocation is appealing since it is practical. There is potential to optimize pro-rata allocations in an easily implementable manner. Ethical considerations for resource allocation during the COVID-19 pandemic have been studied (Day et al. 2020; Boylan 2022; Yuk-Chiu Yip 2021); many of these publications do not use any data-driven modelling methodologies to support their notions of equity. Authors have studied the equitable allocation of scarce resources, such as vaccines (Breugem and Van Wassenhove 2022; Enayati and Özaltın 2020) and ventilators (Yin et al.

2023). Kenan and Diabat (2022) study the supply chain of blood products in the wake of disasters, such as COVID-19, using a stochastic two-stage programming model. They incorporate equity into their modeling by considering objectives for minimizing the maximum unmet demand and minimizing the sum of the total and maximum unmet demand. Li et al. (2022) use supply and demand forecasts in a min-max model to allocate resources. The model is validated through a convalescent plasma distribution case study in the context of the randomized control trial CONCOR-1 in Ontario, Canada. In the aforementioned model, sparse supply and demand data can affect the accuracy of the forecasts, which can result in sub-optimal allocations for trial sites that use little plasma. Kostandova et al. (2023) use a compartmental model to test potential convalescent plasma allocation strategies at reducing infections and mortality. They comment on the relative merit of each strategy with respect to the metric of cost to health benefit.

3 REFLECTING ON CONCOR-1

There is no immediate treatment for a novel pathogen. Historically, the plasma that contains an immune response from individuals who have recovered from an illness, called convalescent plasma (CP), can be given to an infected individual to help fight off the illness. This process is called CP therapy (Ripoll et al. 2021). CONCOR-1 (Bégin et al. 2021) was a randomized control trial to determine the efficacy of treating acute hospitalized patients with a SARS-CoV-2 infection with convalescent plasma therapy compared to the standard level of care in reducing risk of intubation or death. The trial ended early due to futility. CONCOR-1 was a unique clinical trial, in that the trial had expedited Health Canada approvals and was an immediate response measure to provide individuals infected with the SARS-CoV-2 virus with a potentially life-saving treatment when no other treatment was available.

The BC CONCOR-1 Implementation Study (Johns et al. 2022) reflects on CONCOR-1 as a case study to inform future therapeutic trials and pandemic planning by interviewing key CONCOR-1 stakeholders and performing qualitative analysis of the interview transcripts to identify key themes (lessons identified), process mapping the rollout of CONCOR-1 in BC using and unified modelling language activity diagram, and attempting to refine a plasma allocation model (Li et al. 2022) validated on Ontario trial data to the jurisdiction of BC. Trial data was very sparse in BC; therefore, the aforementioned model did not work well for BC CONCOR-1 data. Compared to other provinces BC has many hard-to-reach hospitals due to their rurality, remoteness, or other geographical constraints. We identified the need for practical and readily implementable resource allocation strategies.

4 A PRACTICAL FRAMEWORK FOR EQUITABLE SCARCE RESOURCE ALLOCATION

Resource allocation in healthcare can be hierarchical from the top down: level 1 involves allocating resources to different health authorities, level 2 allocates resources within the health authority, and level 3 is allocating resources to patients. We focus on equitably distributing resources to level 1. In this section, we define a practical framework that results in an equitable fixed interval allocation of resources during a pandemic.

Pro-rata resource allocation is appealing since this notion of equity is readily implementable. Let S be the supply of a resource, K be the number of distinct regions in demand of said resource, and $\mathbf{P} = (P_1, P_2, ..., P_K)$ be a vector of the respective population sizes. Let $\overline{\mathbf{P}} = \mathbf{P}/\sum_{i=1}^{K} P_i$, then $S \cdot \overline{\mathbf{P}}$ can be used to allocate resources, with some rounding. However, pro-rata resource allocation may not be optimal. We can adjust pro-rata resource allocations based upon metrics of equity, as shown in Figure 1. Adjustments are a re-evaluation of the current resource allocation policy in effect to dynamically allocate resources for equity. We consider the metrics of utilization (unmet demand) and cases counts; decision makers can readily turn to these metrics to inform equity in the context of scarce resources in a pandemic. We discuss the process for adjustments later. In the next section, we test our practical framework in a case study for CCP distribution in the context of BC CONCOR-1. Our framework can be applied to most resources.

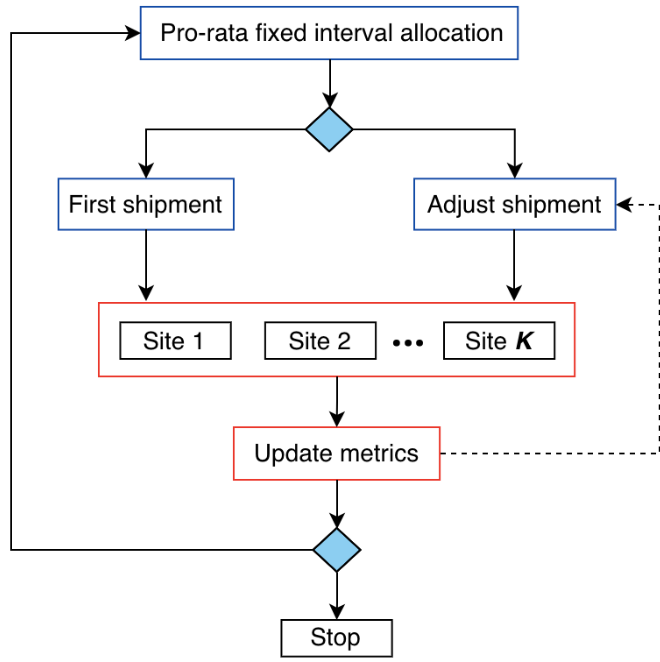

Figure 1: A practical framework for scarce resource allocation during a pandemic on a fixed interval. The blue and red boxes indicate the supplier and demand sites, respectively. The dotted arrow indicates that the activity update metrics will influence the adjustment of the allocation in the next shipment. Stop refers to when there is no more of resource to be allocated or when a resource is no longer needed, e.g., CCP is no longer needed at CONCOR-1 trial sites when the trial has ended.

5 CASE STUDY FOR CONVALESCENT PLASMA DISTRIBUTION

Blood is a crucial life-saving product in most healthcare systems that is needed in both daily hospital procedures and life-threatening emergencies. There are four blood groups: A, B, AB, and O. Blood products include: red blood cells, platelets, plasma, and plasma derivatives. Hospitals must maintain an adequate supply of blood products at all times. Blood products have stochastic supply and demand, compatibility constraints, and a finite shelf life; therefore, finding an optimal inventory policy for these scarce resources is difficult (Beliën and Forcé 2012). Plasma can be frozen and stored for up to one year. Typically, thawed plasma must be used within 24 hours to five days depending on the product and thawed plasma cannot be refrozen. Temperature controlled shipping containers are costly. A blood product can only be given to a blood group compatible patient. Figure 2 shows the compatibility constraints of plasma and details the CONCOR-1 plasma group segmentation.

Inventory management of blood products is a challenge in BC because of the large area of land and varied geography. The five regional BC health authorities are: Fraser, Interior, Northern, Vancouver Coastal, and Vancouver Island Health who approximately serve 38, 16, 5, 24, 17 percent of BC's total population, respectively (BC STATS 2020). Compared to Ontario, the sites in BC implementing the CONCOR-1 trial did not randomize many patients. Not all health authorities in BC participated. We consider the scenario where all health authorities participated in CONCOR-1. We investigate the allocation of CCP in the context of BC CONCOR-1 using our practical framework to ensure the right plasma gets to the right patient in an equitable manner.

Canadian Blood Services (CBS) is the suppler of blood products to all provinces in Canada (except Quebec). The CBS supply is centralized in each province, there is usually only one CBS distribution site that allocates blood products to a province's blood banks. BC CBS Distributions is located within

Vancouver Coastal Health. Some health authority blood banks can be difficult to stock due to geographical constraints with respect to CBS and can experience delays in shipments due to poor weather. Figure 3 shows the flow of CCP during the CONCOR-1 trial. CBS supplies frozen CCP units to hospital hub sites. Each hub site i supplies its spoke hospital sites $1 \ldots j_i$ with CCP. Spoke sites can contact their hub site for CCP as needed. At each trial site, acute hospitalized patients with COVID-19 are contacted to take part in the trial. If recruited, a patient is randomized to be infused with CCP or receive the standard level of care in a two-to-one ratio, respectively.

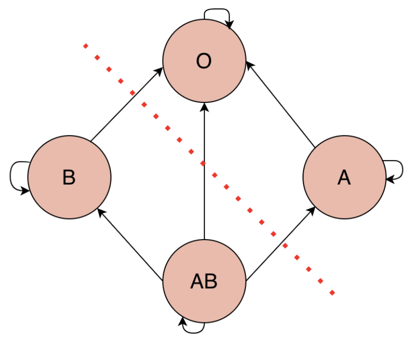

Figure 2: A directed graph of plasma compatibility constraints. A blood group (vertex) can be infused (given) to a patient with the blood group it is adjacent to. To address rarity of group B and AB plasma the BC CONCOR-1 trial considered two plasma groups (dotted line represents the division into groups B-AB and A-O). Group AB plasma can be given to group AB or B, group B can be given to group B, group A can be given to group A or O, and group O can be given to group O patients.

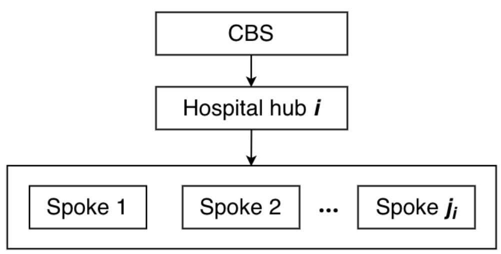

Figure 3: Hub and spoke network for CCP distribution.

5.1 Model

In this section, we present a stochastic simulation model for our practical framework in the context of CCP distribution in BC CONCOR-1. The BC Centre for Disease Control (BC CDC), a program of the Provincial Health Services Authority, provides cases counts segmented by day for confirmed positive COVID-19 infections. We use the online BC CDC case count data (BC Centre for Disease Control 2023) for the CONCOR-1 trial period (August 26, 2020 - January 20, 2021) to calibrate supply and demand of CCP in our model. Figure 4 outlines our methods. We use our model to asses our practical framework for an equitable distribution of resources. Figure 5 provides the flow of activities in our CONCOR-1 simulation. Each week CBS allocates CCP to trials sites using our framework. Trial sites randomize patients to be infused with CPP and update their metrics at the end of the week. This process repeats until the end of our 22 week trial period. We assume the following:

Assumption 1 One hub site per health authority.

Assumption 2 CBS ships plasma once a week to each hub site.
Assumption 3 Hub sites do not transfer frozen plasma outside their health authority.
Assumption 4 Unmet demand from week $t-1$ is not carried over to week t.

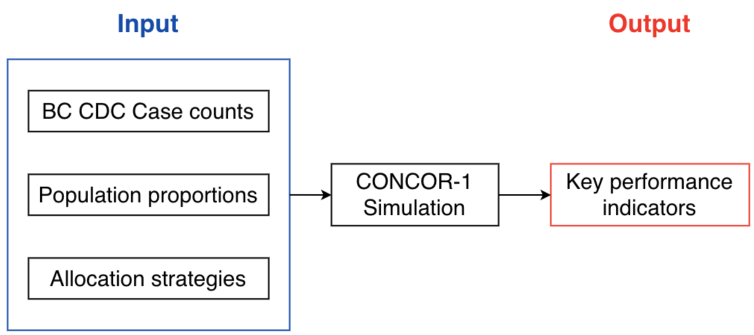

Figure 4: Methods for evaluation of our practical resource allocation framework. The input allocation strategies refers to our processes for adjusting shipments that will be discussed in Section 5.3. Figure 5 outlines our CONCOR-1 simulation.

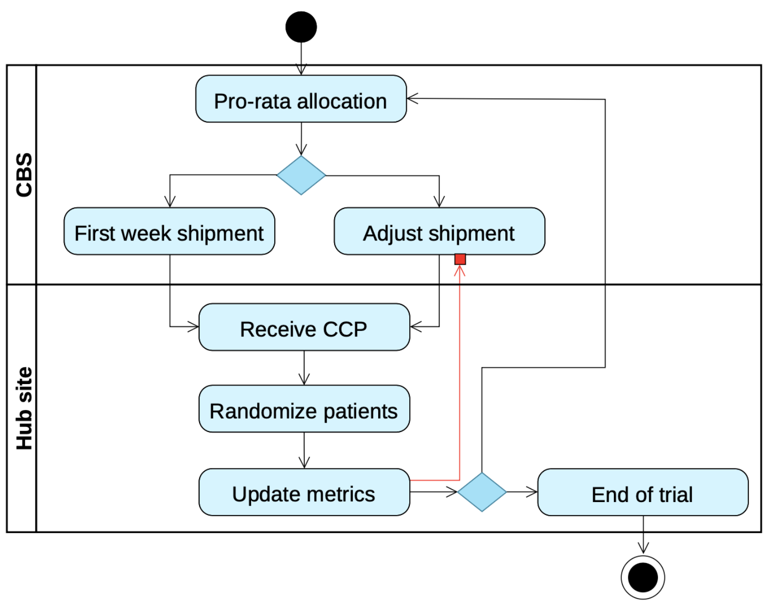

Figure 5: A unified modelling language activity diagram of the events in our CONCOR-1 simulation model. The red arrow flow into the input pin indicates that the activity update metrics will influence the activity adjust shipment.

Assumption 1 is reasonable given the structure of the health authorities and how they manage resources. Moreover, we can view a hub site and all of its spoke sites as a single entity. Assumption 2 is reasonable as CCP is scarce resource during a pandemic. Assumption 3 is generally true in practice since most hospitals are not equipped with proper shipping containers for frozen blood products. Assumption 4 is reasonable since we want to test the merit of our framework on providing an equitable allocation of CCP by quantifying its impact on unmet demand, which we define to be the number trial patients that were randomized but not infused with CCP due to inventory constraints. We note that in the actual CONCOR-1 trial emergency CCP orders were made and a patient was not randomized until a compatible unit of CCP was secured for their infusion (Li et al. 2022).

5.2 Model Calibration

Our model parameters, as outlined below, were calibrated using Ontario CONCOR-1 data. We do not state all the exact parameters used since the product of the calibrated parameters is essentially scaling our weekly demand so that the total CCP demand and supply over the trial period are roughly equal, i.e., CCP units are sufficiently scarce week to week.

The supply of CCP is calibrated using the confirmed COVID cases in BC during the trial period multiplied by a donation probability and a probability that their plasma contains a sufficient level of neutralizing antibodies for COVID-19. This gives us the total amount of CCP available. We divide this by the number of trial weeks, which results in the number of CPP units to allocate each week. Each week, Bernoulli trials (Binomial) are used to determine the number A-O ($p = 0.81$) and B-AB ($1-p$) CCP units.

The arrivals in our model are individuals who are confirmed to have COVID-19, see Figure 6. The arrivals have a hospitalization probability and a hospitalization delay of 5-12 days according to uniform distribution. The arrivals have a recruitment probability and randomization probability, followed by a Bernoulli trial to determine a blood group (A-O ($p = 0.81$) and B-AB ($1-p$)).

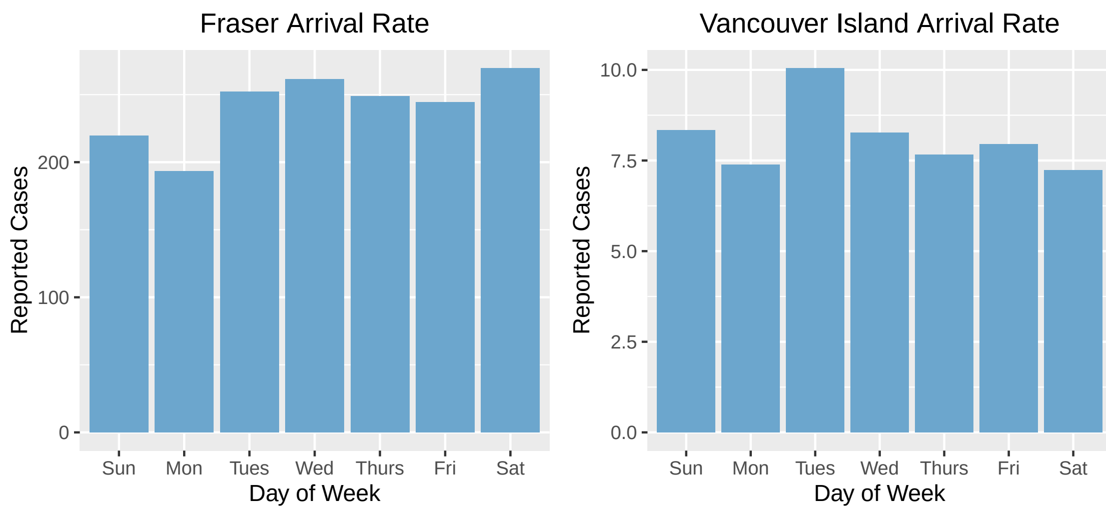

Figure 6: Arrival rates of confirmed positive COVID-19 cases for a health authority with high case counts and a health authority with low case counts during the CONCOR-1 trial. Arrival rates are calibrated to a non-homogeneous Poisson process by day of week using online BC CDC case counts for the CONCOR-1 trial period; in increasing order of total reported cases, the health authorities are: Fraser, Vancouver Coastal, Interior, Northern, and Vancouver Island Heath.

5.3 Adjusting Shipments

One practical way to adjust weekly CCP shipments for equity is using resource utilization. In our case study, utilization occurs if trial patient is infused with CCP. We view utilization from the perspective of unmet demand, the number of trial patients randomized but not infused with CCP due to inventory constraints. Let the *proportion of unmet demand* (PUD) be the fraction of total unmet demand over total demand. For a given week t and blood group, we can adjust the fixed interval pro-rata allocation from CBS to hub sites by pulling CCP units to be allocated to sites that have a "low" PUD and threshold level of inventory onhand; then, distribute (via pro-rata) the pulled CCP units to sites that have "high" PUD. We set the PUD threshold value to be the mean PUD across health authorities in week t, i.e., for each health authority hub, compute the PUD over week 1 to week $t-1$ then take the average. The inventory threshold for a week t for a hub site is the average demand from week 1 to $t-1$. This procedure is given in Algorithm AdjShip.

Algorithm AdjShip

Input: Blood group pro-rata allocation for week t and hub site metrics for for weeks $1,2,\ldots,t-1$
Output: Blood group allocation

```
Compute PUD and inventory thresholds for week t
𝓘 ← ∅
𝓓 ← ∅
for each hub site h do
    if PUD at hub site h ≤ PUD threshold and inventory at hub site h ≥ inventory threshold then
        𝓓 ← 𝓓 + h
    end if
    if PUD at hub site h > PUD threshold then
        𝓘 ← 𝓘 + h
    end if
end for
if 𝓓 and 𝓘 are nonempty then
    Pull resources to be allocated to hub sites indexed by 𝓓 and distribute (via pro-rata) to hub sites indexed by 𝓘
    return Adjusted allocation
else
    return Pro-rata allocation
end if
```

We can also distribute the pulled resources according to the proportion of COVID-19 case counts (CC) within the last two weeks, let us call this procedure Algorithm AdjShipCC. There are other ways to adjust shipments for equity. Our notions of equity are based on how to distribute CCP to where it is most needed subject to the scarcity of resources and data limitations during a pandemic, while balancing availability for patients at each hub site.

5.4 Experimental Analysis and Results

The goal of our experiments is to use simulation to compare the relative merit of allocating CCP in the context of BC CONCOR-1 using (1) pro-rata allocation with no adjustments (NoAdj), (2) Algorithm AdjShip, and (3) Algorithm AdjShipCC within our practical framework. Our simulation model was coded in R. Each scenario 1-3 ran in under an thirty minutes for 500 simulation replications on standard laptop. We evaluate our resource allocation strategies using the performance measures: demand (D), unmet demand (UD), PUD, and ratio of total received inventory to total utilization (TI:TU). We average the performance measures of the simulation replications; in Table 1, the prefix E stands for expected. Unless otherwise stated, the performance measures are computed over both blood groups.

Allocating resources pro-rata (NoAdj), as expected favours hub sites that can potentially serve larger patient populations, which has the unintended consequence of under stocking high-utilization hub sites and overstocking low-utilization sites, as shown by the EPUD and ETI:ETU ratios in Table 1. Algorithm AdjShip decreases the total EUD compared to NoAdj. Algorithm AdjShipCC has EUD and ETI:ETU ratios similar to Algorithm AdjShip, with some differences in EPUD. This is due to Algorithm AdjShipCC allocating more CCP to health authorities that have more confirmed COVID-19 cases in the last two weeks of an allocating period; hence, are expected to have greater need of CCP.

The ETI:ETU ratio for low-utlization sites will be higher, as these sites do not use much but still have some CCP onhand in case the need arises. For the rarer plasma group B-AB, the ETI:ETU is also higher. We observe a more equitable (our notions of equity) ETI:ETU ratio when comparing algorithms AdjShip and AdjShipCC to NoAdj. Figure 7 is a bar plot of the EPUD. This is a visualisation of equity under the different allocation strategies. We ran our simulations for sparse and extremely sparse supply of CCP. As the supply of a resource becomes scarcer, the algorithms AdjShip and AdjShipCC perform similarly and are more efficient (with respect to decreasing total unmet demand) and equitable (our notions of equity) than NoAdj.

Table 1: Simulation key performance indicators plus or minus standard error.

Hub	Algorithm	ED	EUD	EPUD	ETI:ETU	ETI:ETU (A-O)	ETI:ETU (B-AB)
Fraser	NoAdj	134.88 ± 0.30	28.76 ± 0.33	0.2114 ± 0.0020	1.0180 ± 0.0009	1.0060 ± 0.0006	1.0805 ± 0.0057
Interior		29.33 ± 0.14	4.76 ± 0.11	0.1577 ± 0.0033	1.1065 ± 0.0040	1.0806 ± 0.0043	1.3693 ± 0.0310
Northern		20.35 ± 0.13	2.28 ± 0.08	0.1099 ± 0.0037	1.4225 ± 0.0105	1.4501 ± 0.0119	1.2135 ± 0.0231
Vancouver Coastal		55.65 ± 0.21	4.59 ± 0.17	0.0799 ± 0.0028	1.1808 ± 0.0038	1.0950 ± 0.0043	1.6649 ± 0.0315
Vancouver Island		14.61 ± 0.10	0.06 ± 0.02	0.0040 ± 0.0012	2.2598 ± 0.0192	2.0326 ± 0.0326	3.9129 ± 0.1216
Fraser	AdjShip	135.47 ± 0.30	13.87 ± 0.17	0.1020 ± 0.0012	1.0281 ± 0.0010	1.0203 ± 0.0009	1.0738 ± 0.0051
Interior		29.30 ± 0.13	4.79 ± 0.07	0.1648 ± 0.0027	1.2828 ± .0.0101	1.1420 ± 0.0083	2.3180 ± 0.0827
Northern		20.49 ± 0.13	4.80 ± 0.10	0.2330 ± 0.0049	1.5121 ± 0.0194	1.3413 ± 0.0192	2.5982 ± 0.1042
Vancouver Coastal		55.56 ± 0.20	7.51 ± 0.10	0.1350 ± 0.0017	1.0912 ± 0.0032	1.0488 ± 0.0024	1.3474 ± 0.0222
Vancouver Island		14.66 ± 0.10	2.17 ± 0.04	0.1477 ± 0.0024	1.6553 ± 0.0236	1.5680 ± 0.0271	2.3333 ± 0.1010
Fraser	AdjShipCC	135.54 ± 0.30	12.17 ± 0.16	0.0896 ± 0.0011	1.0314 ± 0.0010	1.0234 ± 0.0010	1.0779 ± 0.0050
Interior		29.25 ± 0.14	5.06 ± 0.08	0.1734 ± 0.0027	1.2894 ± 0.0105	1.1557 ± 0.0087	2.2129 ± 0.0742
Northern		20.21 ± 0.13	5.84 ± 0.12	0.2866 ± 0.0057	1.5420 ± 0.0202	1.3863 ± 0.0204	2.4496 ± 0.0938
Vancouver Coastal		55.50 ± 0.20	8.10 ± 0.10	0.1454 ± 0.0018	1.0986 ± 0.0036	1.0523 ± 0.0026	1.3952 ± 0.0269
Vancouver Island		14.77 ± 0.11	2.33 ± 0.04	0.1577 ± 0.0028	1.7592 ± 0.0269	1.6447 ± 0.0331	2.5158 ± 0.0942

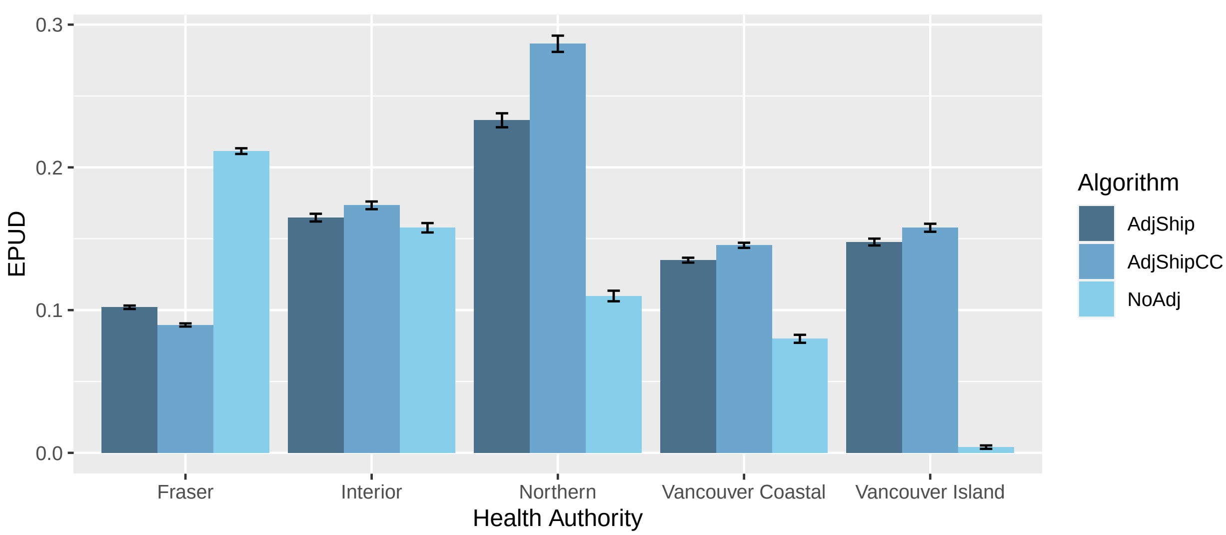

Figure 7: A bar plot of expected PUD for each health authority with standard error bars.

6 DISCUSSION

We have shown that pro-rata resource allocation can be inequitable and inefficient. This resonates with the findings of Wu et al. (2007). In our case study, our practical framework for the allocation of scarce resources outperforms pro-rata resource allocation with respect to decreasing unmet demand, while considering equity over health authorities. Any mathematical formula that solely aims to decrease unmet demand will naturally bias health authorities who have larger patient populations and case counts, e.g., put most of a scarce resource in Fraser Health and Vancouver Coastal Health, which can be inequitable to the more remote/rural health authorities. A similar bias would result if the cost of managing inventory is incorporated into a mathematical formulation.

In our modelling we made some assumptions that can impact equity. Assuming a fixed interval resource allocation will affect equity since emergency orders for blood products can be made in the real world. It would not significantly impact our modelling if we incorporated emergency orders. If resources are sufficiently scarce then emergency orders cannot be filled. We assumed unmet demand is not carried over to the next period, which is not what happened in CONCOR-1 and can be inequitable to patients who were randomized near the next fixed-interval shipment. Nonetheless, our modelling still serves as a good approximation for the merit of our framework for scarce resource allocation.

Recall that our framework takes a tentative pro-rata resource allocation and, if applicable, adjusts the allocation based on utilization and/or case data. This serves as an approximation for a demand site's need for a resource. The underlying notion of equity in our case study can be viewed as a combination of proportional and vertical equity. This is because our definitions of equity are biased towards demand and/or case counts, which can be an oversimplification of equity. Biased notions of equity can result from lack of data collection and data transparency. For example, we do not have real time data for blood group CCP supply, the actual number of COVID-19 patients in ICU, etc. Due to data limitations, we have considered a simplified equity definition using other data to make approximations. Notions of equity in healthcare will come from decision makers and any model used to inform decision making must quantify said notions of equity. A bulk of the relevant literature we discussed pertains to mathematical models that focus on min-max equity, proportional equity, incorporating notions of equity through constraints, or that use simulation to test notions of equity. A broader notion of equity can be difficult to quantify and incorporate into a mathematical model, while utilizing data pragmatically.

Collaborations between decision makers and modellers will allow for appropriate notions of equity to be incorporated into mathematical models. Our framework and its dynamic allocation policies are intuitive/transparent and can be extended to consume actual data. Decision makers can use our framework to evaluate their quantitative notions of equity to proactively inform scarce resource planning during a pandemic.

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