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Location of organ procurement and distribution organisation decisions and their impact on kidney allocations: a developing country perspective

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Abstract

Managing organ transplant networks is a complex task. It intertwines between locating the organ procurement and distribution organization (OPDO) (long-term decision) and allocating organs to the suitable destination (short-term decision). The literature lacks deliberation on the effect of those long-term decisions on short-term ones under the influence of clinical and non-clinical factors. This paper addresses this gap using a k-sum model for locational choice, and a discrete simulation approach for the allocation procedure for a real-life case study from a developing economy perspective. The study explores the trade-off between efficiency (distance-centric models) and equity (the result of time-centric allocation models). Our analysis of the efficiency of locational models and equity of the allocation policies reveal strong inter-dependence of both these decisions, a significant finding of this research. These findings offer an integrated model for high-level decision-makers, which can be used during the locational planning stage and provide input to design standard operating procedures for transplantation schemes.

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1 Introduction

Humans are no longer worried about famine and plague, as longevity has improved over time through medical advancements in knowledge and technology. Nevertheless, deaths due to organ failures are significantly reported across the globe (TCSM, 2019). Organ transplantation remains the most preferred option to treat organ failures (Barker & Markmann, 2013). The process involves harvesting a healthy organ from a donor and transplanting it to a matching recipient selected through an allocation policy that meets key operational factors such as time and distance. Thus, it is imperative to consider the limited shelf life of the explanted organ, which is referred to as *Cold Ischemia Time* (CIT), before it must be distributed and transplanted to a recipient. Owing to this significant control factor, the distribution of explanted organs is limited to a maximum coverage distance in each region, depending on the topography. Thus, it is essential to save human life through controlled distribution measures and replace failed organs within the stipulated time. This scenario is especially true for kidneys, the organ of interest in this paper.

In this context, it is imperative to look at the stages of the overall decision-making process leading to kidney organ transplantations. Two stages of this decision-making process stand out. First, the *Organ Procurement Development Organisation* (OPDO) location stage is an irreversible long-term decision (Belien et al., 2013). The policy entails OPDOs to procure kidneys for transplantation, and organs cannot be transported from one *Transplant Center* (TC) to another. Second is the recipient matching stage, in which explanted organs from deceased donors procured by the OPDOs are assigned to a suitable recipient (Bruni et al., 2006) with due adherence to maximum coverage distance. Any significant deviation in either of these stages may affect the organ supply, widening the demand–supply gap of kidneys and resulting in organ wastages. The gap may also lead to a longer wait time for the patients and reduce the chances of prolonging their lifespan. Nevertheless, the demand for kidneys increases continuously due to new patients needing transplants (Lucey, 2000). Therefore, the location decisions of OPDOs and subsequent organ allocation policies deserve a thorough examination to understand their implications on the design of an efficient and equitable kidney transplant system (Bruni et al., 2006).

To the best of our knowledge, the extant literature does not deliberate enough on the *travel distances of explanted organs* from the OPDOs to the TCs and their consequent impact on *the distribution of waiting times among the patients*. In addition, our review identifies that while integrated location-allocation studies are available in the literature, they do not sufficiently examine the fundamental notions of the trade-off between *distance* and *time*. The authors believe that managing the kidney transplant process in this way captures the complexities of stakeholders' decision-making steps and significantly increases the chances of patient survival in the long run. Thus, policymakers must adopt a customized locational model for equitable organ distribution. Therefore, we propose to address this gap by studying the choice of OPDO locations (and the associated organ travel distances) and their consequent effect on the kidney allocation policies (and the associated distribution of *patient waiting times)* in an integrated manner. More specifically, this work aims to answer the question: *Do OPDO locational decisions made from the family of k-sum models have a trade-off effect on the efficiency and equity of the kidney transplantation process from the perspective of a*

developing economy? In this paper, *'equity'* refers to patients' waiting time across different blood groups (Zenios et al., 2000), and equitable solution refers to '*minimum average waiting time*' for the patients across all the blood groups. Similarly, '*efficiency*' refers to the '*minimum average distance*' traveled by the explanted organ from a designated OPDO to the registered hospital of patients.

The contribution of this paper is multi-fold. Firstly, to our knowledge, this pioneering study addresses equity and efficiency from a long-term, locational impact perspective. Secondly, the deliberations may serve as a reference framework for policy and operational decision-makers to choose health care location models. Thirdly, it is the first to explore the equity and efficiency issue in a populous developing economy and where there is heavy demand for scarce organs such as kidneys. Fourthly, the study provides a customized OPDO locational model for stakeholders that would facilitate controlling the patient waiting time and result in better equity.

The remainder of this paper is structured as follows: Sect. 2 reviews the background literature. Section 3 presents a *k*-sum model for the facility location problem and illustrates its application in a real-life case. Section 4 simulates the real-life application to assess the impact of the location choices on the waitlist patients. Section 5 discusses the results and insights from the models. Finally, Sect. 6 concludes the paper with limitations and future research directions.

2 Literature review

Extant literature on the design of organ transplantation networks acknowledges that the associated decision-making process is a complex one that involves both clinical and non-clinical factors (Afshari & Peng, 2014). Therefore, we find that researchers have approached this problem from the following perspectives: First, the location of the OPDOs is viewed as a strategic or a long-term decision. Second, given the OPDO locations, allocation of the organs is viewed as a tactical or short-term decision. Third, an integrated approach towards location and allocation combines the long-term decisions and ties them with the short-term ones. Further, we also find that healthcare scenarios deserve a specific perspective, depending on the objective of the problem. Thus, this section deals with a brief review of literature deliberating location models, allocation models, and integrated models with both location and allocation choices in the organ transplantation domain, and they are presented in the same order.

2.1 Location models

The location of an OPDO affects the immediate distribution of organs across different regions of a country. Their location is vital in procuring donated organs in a specific area and allocating them on priority to recipients on the waitlist. In general, the classical location models can be categorized into three groups based on their objective functions: set covering (minimizing facility costs), minimal covering (P-center/P-median models), and maximal covering (maximize demands).

Over the years, the locational model studies have evolved to account for various constraints and requirements of the researchers. These studies address different factors and attributes in the following combination: facility cost; demand, and distance [un-capacitated facility location models (Belien et al., 2013)]; minimizing maximum service distance (Toregas &

Revelle, 1972); maximize the distance covered (Church, 1974; Church & Revelle, 1974; Toregas et al., 1971).

Past research has also shed light on facility location models applied to healthcare services. The P-center and P-median models are predominantly used in these services. Further, the research topics on the healthcare location reveal some interesting trends: The earlier studies focus on the location of generic healthcare services (Church, 1974; Church & Revelle, 1974; Heller, 1989; Hodgson, 1986; Hodgson & Rosing, 1992; Huang et al., 2010; Ramos et al., 1999; Sasaki et al., 2010; Toregas et al., 1971; Toregas & Revelle, 1972). Although these studies explore the location under different healthcare scenarios, their primary focus tends to be a methodical contribution, emphasizing benchmarking of their proposed algorithms.

Although such approaches can lead us to an optimal design configuration from the perspective of cost, distance or demand, these approaches do not consider the organ-specific design. The later healthcare location studies have adopted this approach (Refer Table 1) from (a) *single organ-specific location design* and (b)*multiple organ-specific location design* perspectives. Besides, literature has contextualized different organs such as the liver (Belien et al., 2013; Kong et al., 2002; Kong, 2006; Stahl, 2005), kidneys, heart, and lung (Belien et al., 2013). Also, some studies have focused on the CIT factor, unique to organ transplant networks (Belien et al., 2013; Kong, 2006; Kong et al., 2002; Stahl, 2005).

Further, the research in this area attempts to characterize the number of procurement and TCs to be open, which are constrained in various ways. For example, the deliberations by Kong et al. (2002) and Kong (2006) focused on the location of liver TCs, in terms of configuration to maximize not only intra-regional transfers (local primacy); but also inter-regional transfers (national primacy). Further, Stahl et al. (2005) extended the study with a detailed analysis to identify the optimal configuration of transplant regions in the USA, considering OPDO as both procuring and distributing unit, employing national primacy.

In summary, all the locational studies focus on designing the healthcare networks by considering the states as separate regions and employing primacy rules to study the effects of using mathematical models or simulation tools. Also, we observe all these approaches to be algorithmically effective in handling locational decisions. However, the limitation of these methods is that they address only the long-term decisions (OPDO locations) and show less evidence of capturing their impact on the short-term decisions (organ allocations).

2.2 Allocation models

Unlike locational decisions, allocation model decisions are short-term in nature and refer to the task of allocating an explanted organ to recipients based on their clinical history and other factors (Stegall, 2005). In general, the extant allocation literature underscores the importance of appropriate allocation policies which make the transplantation procedure successful (Meyers et al., 1999). Further, the allocation procedure is specific to the type of explanted organs and clinical factors of patients, which is due to the variation in the CIT for different organs (Colajanni & Daniele, 2021; Watson & Dark, 2012). Furthermore, our review finds that the allocation literature considers at least one clinical factor for organ transplantation.

The literature shows two modeling approaches for allocation policies, qualitative and quantitative (Table 2). Similar to location literature, we find a distinct trend with past studies focusing on qualitative models and adopting rigorous quantitative models later. It is pertinent to note that significant advantages of pursuing a qualitative allocation policy are: (a) Qualitative approaches can be easily changed or updated under prevailing clinical advances

Table 1 Literature on location models

Sources	Problem/Objective/Method/Organ/Factors	Major findings
Belien et al. (2013)	Problem: Designing TC locations; Objective: Minimize travel time between donor notification and donor arrival; Method: MILP model; Organ; Multiple; Factors: Clinical and Non-clinical;	When cold-ischemia times are important, it is better to open fewer centers, and this comes at the cost of a lower service level. When travel times are important, opening more centers is optimal, which increases service level
Toregas & Revelle (1972)	Problem: Location of Emergency healthcare services; Objective: Minimize maximum service distance; Method: Linear Programming, Reduction rules; Organ: None specified; Factors: Non-clinical	Linear programming, along with reduction techniques, can give better quality solutions
Church & Revelle (1974); Church (1974); Toregas et al. (1971)	Problem: Public facility location; Objective: Maximize the total distance served; Method: MILP and Heuristics; Organ: None; Factors: Non-clinical	Proposed heuristic algorithms perform well when data contains dense areas where a central facility can be located. Also, addressing mandatory coverage constraint in the mathematical model yield better solutions than classical set covering problems
Sasaki et al. (2010)	Problem: Emergency response service location; Objective: Enhance Emergency service by reducing ambulance response times; Method: Genetic Algorithm; Organ: None; Factors: Non-clinical	Data-driven ambulance reallocation strategy resulted in a significant reduction in the average time to respond to calls
Kong et al. (2002); Kong (2006)	Problem: Liver transplantation center location; Objective: Maximize total liver transplants invoking inter/intra-regional transfers; Method: MILP; Organ: Liver; Factors: Clinical	The number of liver transplant coverage increased using a limited number of centrally located TCs
Stahl (2005)	Problem: Liver transplantation center location; Objective: Methodological framework for determining optimal location configuration maximizing allocation efficiency; Method: Integer Programming model; Organ: Liver; Factors: Clinical and Non-clinical	Results indicate the presence of a trade-off between allocation efficiency and geographic equity
Heller et al. (1989)	Problem: Locating emergency medical service; Objective: Minimizing mean response time is the primary objective and considering workload constraints; Method: Two models: P-median transportation problem in conjunction with simulation; Organ: None; Factors: Non-clinical	The p-median transportation model performs well in predicting mean response time reduction under facility workload restrictions

Table 1 (continued)

Sources	Problem/Objective/Method/Organ/Factors	Major findings
Hodgson (1986)	Problem: Location design under facility sizes and patron distances; Objective: Optimization under different facility sizes and patron distances; Method: Successive inclusion of facilities using modified gravity models; Organ: None specified; Factors: Non-clinical	Modeling hierarchies with a negative exponential version of gravity models result in consistent predictions
Hodgson & Rosing (1992)	Problem: Location of service facilities; Objective: Minimize the cost of serving two different types of demand when selecting the location of facilities; Method: MILP; Organ: None specified; Factors: Non-clinical	The p-median model is more susceptible to inferior solutions than flow-capturing solutions for the small-scale problems tested
Huang et al. (2010)	Problem: Location of emergency health care systems; Objective: Location design under large-scale emergency scenario; Method: Dynamic programming and MILP; Organ: None specified; Factors: Non-clinical	Proposed dynamic programming algorithm able to get reasonable quality solutions compared to other exact methods
Ramos et al. (1999)	Problem: Location of Secentersentres; Objective: Minimize distances; Method: Multi-objective 1-median Model; Organ: None specified; Factors: Non-Clinical;	Proposed algorithms can efficiently locate facilities under multiple median-type objectives

(Pritsker et al., 1995). (b) They also offer advantages in terms of measurable progress in the access to organs by different demographics (Poli et al., 2009; Starzl, 1987). (c) Although qualitative studies are subjective and difficult to replicate in a different scenario, they enjoy the advantage of user-friendly nature, easily decoded by decision-makers (Pritsker et al., 1995).

In the qualitative models, allocating explanted organs is done by assigning points to patients and is the widely adopted approach. In addition, these models tend to differ in the type of factors considered for organs. For instance, Pritsker et al. (1995) studied the problem of allocating livers based on a patient's score on multiple dimensions based on clinical status, waiting time, and blood type compatibility with donors. A candidate ranked first or highest by the allocation policy is offered with the recovered organ. In another qualitative model, Starzl et al. (1987) proposed a multifactorial system for allocating cadaveric kidneys based on clinical and non-clinical factors such as waiting time and logistical factors.

Contrary to the qualitative approaches, we find that quantitative approaches focus on myopic allocation aspects. Nevertheless, these studies have explored characteristics of the allocation policies with greater analytical depth. For example, Zenios et al. (2000) studied the performance of kidney allocation policies on *clinical efficiency* and *equity* criteria. Similar to our study, equity from their context is the *mean waiting times* across patient types. They found that the points allotted for waiting time exceeded every other criterion and prioritized those who came first on the waiting list. In a related study, Zenios (2002) developed a *Monte Carlo* simulation model for validating four different kidney allocation policies that differ in the extent of control kidney exchanges. The patient and donor characteristics were dynamically simulated in addition to the patient and graft survival rates and quality of life. The proposed method was found to be effective in comparison with the existing points-based system.

Table 2 Literature on allocation models

Sources	Problem/Objective/Method/Organ/Factors	Major findings
Pritsker (1995)	Problem: Performance of Allocation Policies; Objective: Identifying efficient organ allocation policy; Method: Multi-criteria Point Ranking Scheme; Organ: Liver; Factors: Clinical;	Allocation policies perform similarly in predicting total deaths; No change is warranted in the existing system;
Starzl (1987)	Problem: Method: Ranking scheme;Objective: Multifactorial Equitable Selection; Organ: Kidney; Factors: Clinical and Non-clinical	Multifactorial equitable selection policy performed well in comparison to manual for over 95% of the cases; Exceptions were managed by surgeons
Aldea et al. (2001)	Problem: Conceptual (Multi-agent Architecture); Objective: Achieving coordination between stakeholders (agents); Organ: Multiple; Factors: Clinical and Non-clinical;	Proposed multi-agent architecture able to perform better coordination between different stakeholders
Zenios et al. (2002)	Type: Queuing model; Objective: Organ allocation; Organ: Kidney; Factors: Clinical	A centralized system that tightly controls the exchange system's size and invokes indirect exchanges when appropriate experiences short waiting times
Zenios (2000)	Objective: Efficiency (Clinical) and Equity (Likelihood of transplant, Waiting time); Organ: Kidney; Factors: Clinical and Non-clinical	Equity—Efficiency trade-off can be alleviated by employing an appropriate organ allocation policy that explicitly addresses this trade-off
Davis et al. (2013)	Problem: Impact of allocation policy changes at the system level for wait times; Objective: Allocation model to assess wait times; Method: Discrete event simulation; Organ: Kidney; Factors: Clinical	Waiting times of AB and B blood groups are difficult to predict compared to O and A blood groups
David & Yechiali (1985)	Problem: Decision on acceptance-rejection of a kidney offer for a single patient; Objective: Devising optimal policies for a decision on kidney offer; Method: Birth–death process; Organ: Kidney; Factors: Clinical	Identification of time frame for acceptance-rejection of a kidney offer
David & Yechiali (1995)	Problem: Decision on acceptance-rejection of a kidney offer for multiple candidates; Objective: Devising optimal policies under different supply–demand scenarios; Method: Sequential stochastic assignment model; Organ: Kidney; Factors: Clinical	The total expected reward based on immediate and delayed offers is optimal for a minimal supply of organs. This reward will be higher for patients with rare clinical attributes;
Poli et al. (2009)	Problem: Developing Advanced Clinical Kidney allocation algorithm; Objective: Efficient kidney allocation; Method: Advanced clinical factor algorithm; Organ: Kidney; Factors: Clinical	The proposed method has the potential to use the organs judiciously
Colajanni & Daniele (2021)	Problem: Distribution of Organs from TC to Transplant Centers; Objective: Minimizing distribution Cost; Method: MILP under uncertainty; Organ: Multiple; Factors: Clinical and Non-clinical	The proposed mathematical model can find reasonable solutions for small-scale test problems

Later, decision support systems were also implemented based on the simulation models. For instance, Davis et al. (2013) developed a simulation model, KSIM, that involved the input of data characteristics, kidney transplant system simulation framework design, and output analysis on the effect of geographic disparities and alternative organ allocation policies. The proposed model was used to study the effect of different allocation policies on the waiting time of the patients in the waitlist.

Recently, the allocation literature pointed to optimizing the organ transplant network's distribution cost during the transplantation process (Colajanni & Daniele, 2021). The authors propose a mathematical model to allocate the explanted organs across different healthcare facilities to minimize the total distribution cost while taking care of clinical factors.

Allocation policies in all these studies assume that once organ matching is successful, the offered organ is accepted by the patient. However, the patient also has an option to reject and wait for a better match. Such an approach is found in the works of David and Yechiali (1985, 1995). The fundamental notion is to model acceptance as a stochastic process. However, as the authors observe, the optimal policies devised in these studies are analytically intractable for large-scale problems.

The allocation literature has also recognized the difficult task of coordination between various stakeholders for transplantation, which results in complexities ranging from legal, clinical, and organizational to human dimensions. Therefore, extant literature has also proposed a multi-agent perspective to address these issues (Aldea et al. 2001).

As mentioned above, the review confirms that the allocation policies are short-term, the decisions during this process span a few days, and the focus is primarily on clinical matching. Although distributional aspects are also addressed (Colajanni & Daniele, 2021), it is not clear from these studies how the long-term, irreversible location of key central facilities such as OPDO impacts organ travel distances and patient waiting times, which is our paper's focus.

2.3 Location and allocation models

In the light of the observations made in previous sections, researchers have long stressed the need for integrated location and allocation decisions in healthcare (Afshari & Peng, 2014). Further, integrated location-allocation decisions deserve due attention for several reasons:

- Firstly, since location decisions are not easily reversible, they have a long-run effect on the subsequent allocation mechanisms, especially amidst the growing demand–supply gap.
- Secondly, the number of OPDOs has a direct relationship with the availability of deceased donors for the OPDOs and thereby affecting the number of transplanted patients later; and
- Thirdly, it is of interest to the policymakers to study the location of healthcare facilities and its impact on equity and efficiency issues, which can be understood entirely by incorporating the allocations mechanism in the locational decision-making process.

In an earlier study addressing this gap (Table 3), Bruni et al. (2006) developed a TRALOC model, based on P-median, to locate and allocate organs by considering the roles of procurement and distribution of OPDOs in Italy. They stress the proper location of OPDOs in ensuring a fair (minimizing distance) and equitable transplant system (minimum waiting time). However, the objective function in their study does not capture the flexibility of selecting one of the P-center, P-median, and P-center-beta models. An essential distinction in our study is the ability of the locational model to explicitly capture this selection using a parameter called 'k' that can be useful for policymakers.

Furthermore, Belien et al. (2013) propose an integrated location and allocation model to minimize an organ's time outside the body. Under this condition, the authors suggest that

Table 3 Literature on integrated location-allocation models

Sources	Problem/Objective/Method/Organ/Factors	Major findings
Afshari & Peng (2014)	Problem: Review of Literature; Objective: Synthesis of literature; Organ: Multiple; Factors: Clinical and Non-clinical	Lack of comprehensive models that integrate location considerations with tactical or operational considerations
Bruni et al. (2006)	Problem: Identification of TC location while balancing wait list; Objective: Minimize the distance between center to center while minimizing wait list length; Organ: Multiple (Kidney, Liver, Heart); Factors: Clinical and Non-clinical	Models that consider wait list length explicitly have the potential to reduce the length compared to models that do not;
Belien et al. (2013)	Problem: Identification of TC location; Objective: Minimize the time organ becomes available until transplantation into recipient's body; Method: MILP; Organ: Multiple (Kidney, Liver, Lung, Heart, Pancreas); Factors: Clinical and Non-clinical	When CIT is relatively more important than total travel times of organ and recipient, centralizing the facilities is better but at a lower service level
Zahiri et al. (2014)	Problem: Design of transplant networks under uncertainty; Objective: Minimize total cost and waiting time for transplantation; Method: Multi-objective, Multi-period location-allocation model; Organ: Multiple; Factors: Clinical and Non-clinical	Both stochastic models were proposed to yield the same number of TCs for Iran. Under uncertainty, the stochastic model results are similar to deterministic models with the centralization of facilities for congested areas. For sparse areas, one stochastic model yields reliable results with more TCs accessible to patients
Aghazadeh et al. (2017)	Problem: Design of transplant networks including clinical factors; Objective: Reduce total cost, maximize the number of expected donors and minimize total organ shipping time; Method: Multi-objective MILP; Organ: Multiple; Factors: Clinical and Non-clinical	Total organ shipping times exhibit more sensitivity to parameters followed by the number of expected donors; Total cost of transplant is the least sensitive of all
Hodgson & Jacobsen (2009)	Problem: Capturing Irrational behavior of recipients in location-allocation design; Objective: Minimize the negative effect of irrational behavior (patrons traveling to farther facilities termed as irrational); Method: Hierarchical P-median model; Organ: None specified; Factors: Non-clinical	Modeling the irrational behavior of recipients results in the total distance traveled by recipients increasing slightly
Rouhani et al. (2021)	Problem: Organ transplantation network design; Objective: Maximize network responsiveness while minimizing total cost; Method: Possibilistic programming; Organs: Multiple; Factors: Clinical and Non-clinical	Among the three possibilistic programming methods proposed, the realistic approximation method provides better solutions

the centralization of facilities may result in less patient travel time. Our objective differs by addressing organ travel distances and patient wait times for organ delivery in the decision-making process. While the locational decision stage considers distance explicitly, wait times are the result of allocation policy in our model. Related studies have also addressed multiple objectives: Zahiri et al. (2014) propose a multi-objective cost and time model in designing a transplant network under uncertain conditions. A related study by Aghazadeh et al. (2017) developed a multi-objective model for organ transplantation networks. The model had three objectives for designing an effective decision-making system. Their study reveals that organ shipping times prioritize the number of expected donors and the total cost of transplants.

Recently, Rouhani et al. (2021) proposed a bi-objective model for organ transplant network design, focusing on maximizing network responsiveness while minimizing the total cost of transplantation with due consideration of clinical and non-clinical factors. These studies examine the impact on equity or clinical efficiency in a multi-organ context. Although multi-organ network design covers a wide range of requirements, it is argued that designing a single organ transplant network may result in a more equitable system (Bruni et al., 2006). Therefore, this was one of the motivations to look at a single organ context (kidney). Thus, our study differs from these by examining efficiency in the notion of distance traveled by explanted organs and equity in terms of patient waiting times to receive the organs using clinical and non-clinical factors in kidney transplantation.

In summary, our detailed literature survey reveals a notable gap in understanding the consequential effect of locational choice on kidney allocation in the decision-making mechanism and the implicit trade-off between equity and efficiency. These proposed models also lack inherent flexibility in choosing locational models in the first stage. Further, it is unclear from the existing studies whether building such flexible locational models can influence efficiency and equity. We posit that building flexible locational models is the key to unlocking more OPDO choices that can positively influence the patient waiting times and reduce organ wastage. Therefore, the study endeavors to address this gap.

3 Models for efficiency and equity in organ transplantation

Our proposed integrated model relies on a single iteration mechanism, where we first choose a set of OPDOs from the available list of all TCs using a mathematical model. The chosen set of OPDOs is then used for the organ allocation process to study the distribution of waiting times. Figure 1 depicts the overall modeling process.

We propose a mathematical model for locating OPDOs that fundamentally addresses the notion of 'distance' to capture the 'efficiency.' Traditionally, the model belongs to a family of *the k-sum model* used for locational decisions in the literature.

3.1 Location models

We use a generalized version of the P-median model, the *k-sum* model, which is flexible enough to characterize the averages by optimizing the sum of 'k' worst outcomes and is ideally suited to study the problem we address. Such an approach towards optimizing 'k' worst outcomes enables the decision-maker to select one of the following locational models: (1) P-center model, (2) P-median model or (3) P-center-beta model.

Specifically, we use a version of the *k-sum* model rooted in the idea proposed by Fillippi et al. (2017) to study the effect of locational decisions on the subsequent kidney allocation
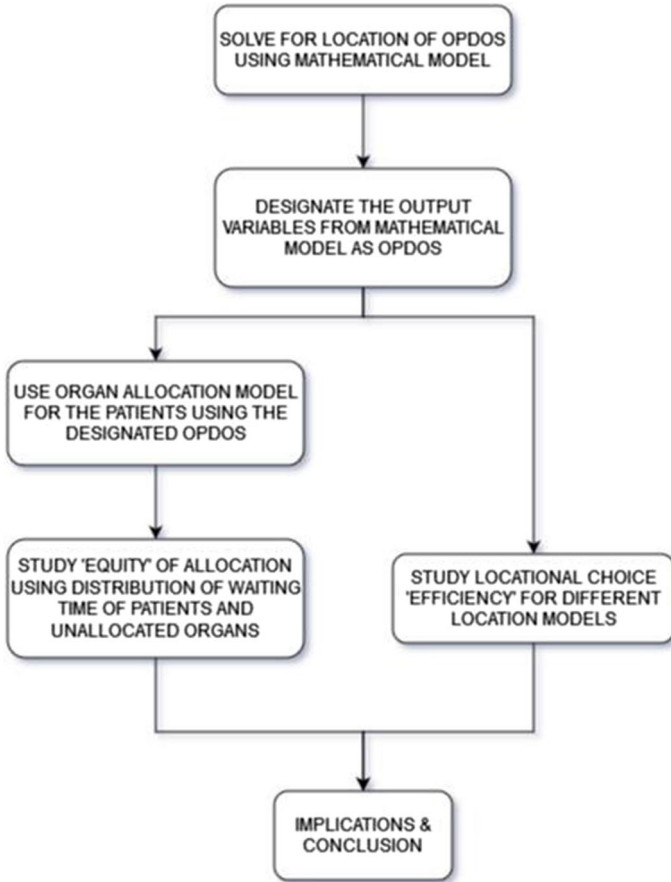
Fig. 1 Decision-making Process for Efficiency and Equity in Kidney Transplantation

stage. The P-median, P-center, and P-median models can be derived from this base model by changing the value of *'k.'* The notations, variables, and indexes used in this paper are given here.

3.1.1 Indices

i, Demand TC index range 1,…N
j, OPDO index range 1…M

3.1.2 Sets

N, Total number of TCs
M, Number of OPDOs

3.1.3 Parameters

D_{ij}, Distance between demand TC i and OPDO j
P, Number of facilities (OPDOs) to locate
C, Coverage constraint on the Cold Ischemia Time (CIT) in terms of distance.
k, Number of TCs to be considered as the average maximum distance.

3.1.4 Decision variables

u, A continuous variable to optimize obtaining the *minimum of the maximum* distances.
v_i, A continuous variable to obtain the *most significant average outcome* of the subset of k outcomes for TC i.
X_j, A binary variable takes 1 if the OPDO j is designated, 0 if not
Y_{ij}, A binary variable that takes 1 if the demand TC i is covered by the OPDO j or 0 if not

3.2 *k-sum model*

$$\min k * u + \sum_{i=1}^{n} v_i$$

Subject to:

$$\sum_{j=1}^{m} Y_{ij} = 1, \forall i, \; i \; in \; 1, \ldots, n \tag{1}$$

$$Y_{ij} \leq X_j \forall i, \; j, \; i \; in \; 1 \ldots n, \; j \; in \; 1 \ldots m \tag{2}$$

$$\sum_{j=1}^{m} X_j = P \tag{3}$$

$$D_{ij} * Y_{ij} \leq C \; \forall i \; in \; 1 \ldots n, \; j \; in \; 1 \ldots m \tag{4}$$

$$k * u + k * v_i \geq \sum_{j=1}^{m} D_{ij} Y_{ij} \forall i, \; i \; in \; 1 \ldots n \tag{5}$$

where,

$$X_j = \begin{cases} 1, & \text{if OPDO } j \text{ is assigned} \\ 0, & \text{Otherwise} \end{cases}$$

$$Y_{ij} = \begin{cases} 1, & \text{if demand transpant center } i \text{ is covered by OPDO } j \\ 0, & \text{Otherwise} \end{cases}$$

$$u \geq 0$$

$$v_i \geq 0$$

The objective function minimizes the average and maximum distance of the worst-case outcome. Constraint (1) ensures that the demand of each TC is satisfied by exactly one of

the designated OPDOs among the candidate TCs. Constraint (2) stipulates that the demand at each TC is taken care of by the designated OPDO associated with it. Constraint (3) is the number of OPDOs to be located and is specified by the modeler. Since the explanted organ must travel to the hospital within the CIT, this coverage constraint is taken care of by (4). Constraint (5) ensures that the sum of average and maximum (worst-case) distance for a given TC is at least as significant as the total distances of all the TCs served from designated OPDOs. A critical observation in this location model must be recorded here is that CIT is treated indirectly as a distance rather than the actual time.

4 The organ transplantation case of Tamil Nadu

The analysis primarily depends on the value of 'k,' the primary decision-making parameter in selecting the one among three, i.e., P-center, P-median, or P-center-beta models. Lower values of k make the model minimize the worst-case distance, and higher values of k drive the model closer to minimizing the average distance. Thus, $k = 1$ implies the P-center model, and $k = N$ indicates a P-median model. Any value of k between 1 and N indicates a trade-off with a new model, namely the P-center-beta model. This flexibility in the model specification captures the underlying tension of distance (captured explicitly in the locational stage) and waiting time (implicitly as a derivative of the locational model studied in the allocation stage). We choose to explore this model in the context of OPDOs located in Tamil Nadu state, India, for the reasons discussed in the following paragraph.

Tamil Nadu is one of the 29 states in India, having a population of 67.9 million, and is also one of the most developed states of India in terms of the Human Development Index. The choice of this state for the case study is motivated by the number of transplants post-2008. The state has seen many surgeries in the recent past (Srinivasan, 2013). This state has set the standards for others because of its pioneering effort to increase the number of donations in the form of the *Cadaver Transplant Program* (CTP). Fifty-eight hospitals, which act as TCs, have registered for organ sharing in the Cadaver Transplant Program. About 29 of these TCs are concentrated in Chennai, and the remaining are dispersed in other state regions. Without loss of generality, we assume $k = 1$ for the P-center model, $k = 29$ for the P-center-beta model, and $k = 58$ for the P-median model for the rest of the analysis study.

Since most TCs are in the Chennai district, collectively, we call the TC in this district a 'dense cluster' and the rest of the TCs a 'sparse cluster.' Tamil Nadu has been divided into three zones, North, South, and West comprising different districts for effectively utilizing the harvested organ without wastage. Each zone currently comprises one major OPDO that takes care of the transplantation process and follows local primacy rule (i.e., priority for patients in respective zones) for kidney allocation.

The geographic location and demand data are downloaded from the *Tamil Nadu Network for Organ Sharing* (TNOS) and the *Transplant Authority of Tamil Nadu* (TRANSTAN) website (TNOS, 2018; TRANSTAN, 2018). Further, distances between TCs and designated OPDOs are computed from a pairwise-distance matrix. The coverage distance for the organ has been fixed at an upper limit of 300 km, as a proportional value of CIT.

In addition, we study the model sensitivity towards the number of TCs to be designated as OPDOs. This is done by varying the values of 'P' (i.e., $P = 2, 3$ & 4) to check the robustness of the location model and the consequential impact it has on the subsequent allocation process.

The mathematical model was implemented using the public domain data on the patient waiting lists of 1825 patients in the ILOG CPLEX OPTIMIZATION STUDIO software. The

Table 4 Descriptive Statistics for distances in K-sum (P = 3) approach

	K = 58 (P-median)	K = 1 (P-center)	K = 29 (P-center-beta)
Mean distance	35.65	50.55	37.28
Standard deviation (SD)	56.14	56.15	54.26
Sample variance	3152.49	3153.08	2944.79
Minimum	0	0	0
Maximum	209.98	146.60	212.76
Coefficient of variation (SD/Mean)	1.57	1.11	1.45

model solution will consist of the value of 1 for binary variables associated with the terms X_j and Y_{ij}. We use this information to compile the distances between each TC and their designated OPDO to arrive at the results presented in Table 4 for a 3-OPDO scenario. We chose this for presentation because there are three designated OPDOs currently in operation in Tamil Nadu.

Table 4 allows us to examine the *efficiency* of the locational model. The P-median model outperforms other models in the primary metric, namely, the mean distance of 35.65 kms travelled by the explanted organs. This result was expected because it considers all the candidate TC for distance minimization. However, as shown in Table 4, the worst-case (maximum) distance is higher for the P-median and P-center-beta models than for the P-center model, which has the lowest value. It is observed that the standard deviation is comparable across all three models. Further, we expected the P-center model to outperform the P-median model in the metric CV because of the minimization of worst-case distance (a single hospital outcome), which may increase the mean distance. It turns out that the CV is indeed the lowest for the P-center model compared to others, with 1.11. Thus, the P-center model scores better on two other metrics. This indicates that the P-center model is the best choice if maximum coverage distance or CV is of priority.

The initial results applying the locational model to real-life data for a three OPDO requirement reveal the performance of the P-median model as superior compared to others from an efficiency perspective when mean distance is used for comparison. However, as we contend, an efficient model need not be equitable because the equity aspect of waiting time or clinical attributes is not addressed in the model. The remainder of the analyses attempts to validate this hypothesis. The TCs selected by the model is the designated OPDOs for the allocation procedure.

4.1 Allocation model for equity in organ transplantation

An allocation model is a natural consequence of facility location. Our study implies the designation of OPDOs as hubs and the associated TCs as spokes. The organs arriving at OPDOs are allocated for the patients registered in the associated TC. Thus, the locational choice made in the previous model has an important bearing on the long-term outcome of organ allocation because the efficiency is already '*fixed*' by the locational model at this stage. In our allocation model, we use a discrete probability simulation to study the effect of OPDO locational choice on the equity of allocation. A fair allocation of the organs to all the patients

Table 5 Sample of Simulated Donor Arrivals

Organ number	Date of arrival (Forecasted using CMA)	Blood group (Simulated)	OPDO zone (simulated)	Hospital (simulated)
1	01-01-2014	A	North	Apollo
2	01-01-2014	O	North	Apollo
3	01-01-2014	B	North	Apollo
4	01-01-2014	O	North	Apollo
5	01-01-2014	O	North	Apollo
6	01-01-2014	B	North	Apollo
7	01-02-2014	A	North	Apollo
8	01-02-2014	O	North	Apollo
9	01-02-2014	B	South	Frontline
10	01-03-2014	B	North	Apollo

should result in an 'equitable waiting time distribution of average waiting time' for all the blood groups in all the zones.

4.1.1 Data source

This model aims to test the allocation policy based on public data from the Tamil Nadu state health care department (TRANSTAN). The organ transplantation data of 2014 (275 kidney donations) consisting of historical donor monthly arrivals and their blood groups, individual hospital contributors, and benefactors' data forms the basis for simulating organ arrivals. We assume this data represents a best-case scenario because, after 2015, no detailed statistics regarding donor arrivals were published on the website.

Monthly donor data with details on the blood group and the contributing hospital from January 2014 to March 2014 and April 2015 to December 2016 is computed through forecasting (Central Moving Average). Without loss of generality, we assume that the arrivals happen during the first day of each month. For instance, if we assume there are three deceased donors in January 2014, six kidneys will be available on January 1, 2014. Further, the blood group and OPDO zone to which these donor arrivals belong are simulated using the historical data from this report (Appendix 1, Table 1) using a simple discrete probability simulation. A sample of the forecasted donor arrival data for January and February is provided in Table 5.

These generated organ arrivals are allocated to recipients from waitlist data on the TRANSTAN website (Table 6). The waitlist consists of individual patient details with the registration date, hospital, and blood group. The rank within a zone, computed based on the blood group & hospital zone combination by TRANSTAN, is also available on the waitlist.

4.1.2 Recipient matching process

Once a donor organ arrives with a specified date and blood group at a designated OPDO, it is ready for the recipient matching process. Recipient matching is crucial in transplantation as it impacts the equity and efficiency trade-off. The recipient matching process in our study closely mimics the actual matching process and is governed by the assumptions already listed in Sect. 3.3.1, adding the assumptions mentioned below.

Table 6 Sample of Waitlist of recipients maintained in the registry

Sl. no.	Blood group	Hospital	Registered date (mm/dd/yy)	Hospital zone	Rank within zone
1	O	Kovai Medical Center and Hospital, Coimbatore, India	11/30/2009	West	1
2	A	Dr. Jeyasekharan medical trust, Nagercoil, India,	11/30/2009	South	1
3	O	Sri Ramakrishna Hospital, Coimbatore, India	11/30/2009	West	2
4	A	Kidney Care Center, Thiruvananthapuram, India	11/30/2009	South	2
5	B	Kidney Care Center, Tuticorin, India	11/30/2009	South	1

4.1.3 Assumptions in the recipient matching process

- Recipients receive the organs from their designated OPDO based on the solution of the mathematical model.
- Each organ arrival is considered an individual, discrete event.
- The patient always accepts the kidney offered.
- Every organ is deemed as '*shared*.'
- Organs are equally likely to be allotted to anyone within the zone, following the First Come-First Transplant (FCFT) policy.
- For allocation, only perfect matching is allowed (O–O, A-A, B-B, and AB-AB Blood groups).

4.2 Steps for recipient matching

Broadly, the steps for recipient matching involved in recipient matching are:

Step 1 Prepare a **Separate Waitlist** consisting of Zone-wise, and Blood-group wise potential recipients.

Step 2 Prepare a **Combined Waitlist** consisting of Blood-group wise potential recipients from all zones combined.

Step 2 For the next donor arrival in the selected zone, check for the first perfect blood group match from the **Separate Waitlist** of the respective zone. If a match is found, make the allocation and repeat Step 2; otherwise, go to Step 3.

Step 3 For the selected donor arrival, check for the first perfect blood group match from the **Combined Waitlist**. If a match is found, make the allocation and go to Step 2.; otherwise, list the organ as 'Unallocated' and go to Step 2.

Step 4 If all arrivals are completed in the donor list, select the next zone, and go to Step 2. If no more zones remain, Stop.

A detailed step-by-step approach to this recipient matching process is shown in Fig. 2. The allocation model solution facilitates the comparison of equity and efficiency. We calculate
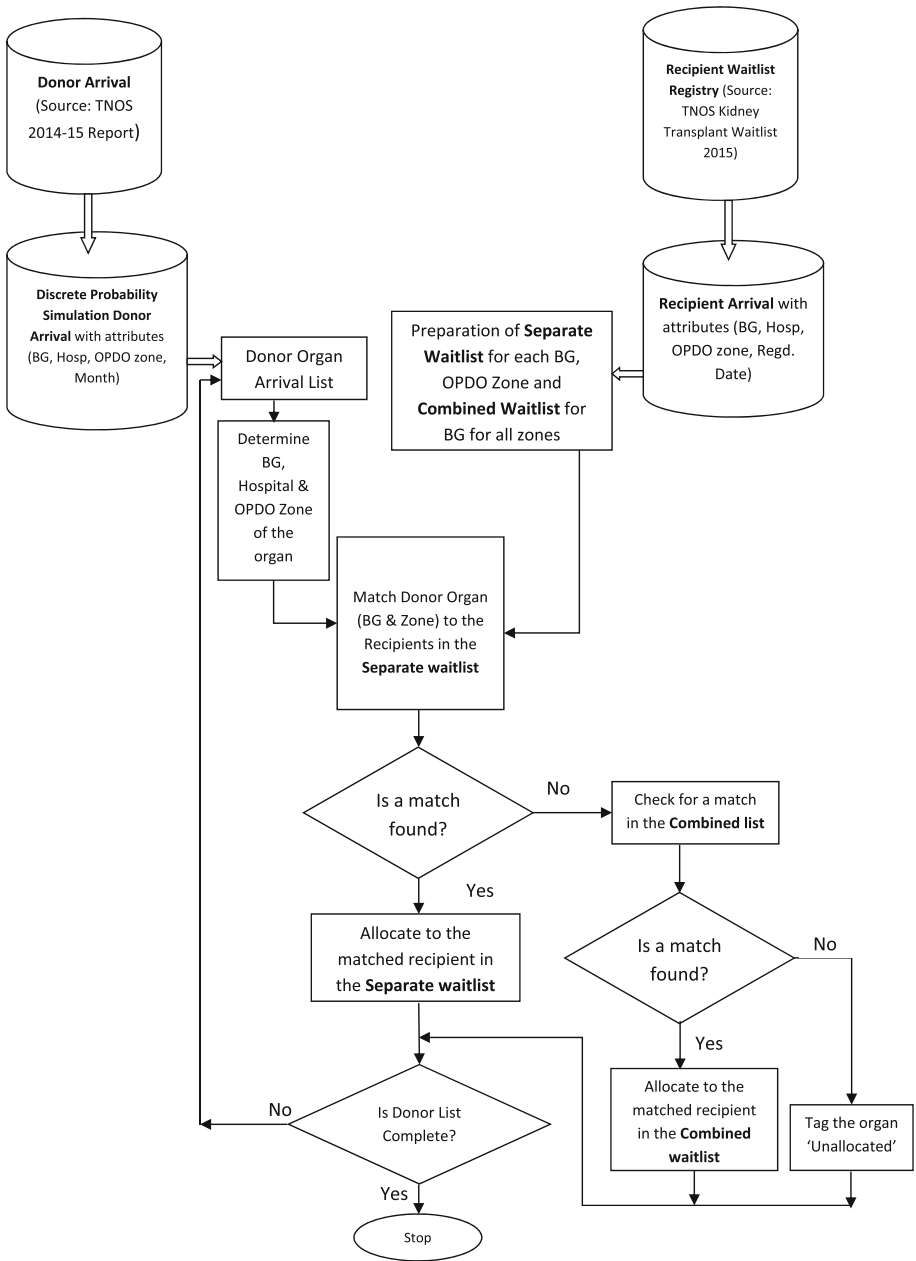
Fig. 2 Allocation procedure—Process chart

patients' waiting time as the difference between the registration and the allocation in days. Further, these results are also used for computing 'unallocated' organs for each model.

5 Results and discussion

The simulation was conducted using MS Excel software on a laptop with a Windows configuration. New arrivals were generated using the random number function in MS Excel, adhering to the arrival patterns published in the report, as mentioned earlier. The simulated allocation is applied for all three scenarios of the number of OPDOs ($P = 2, 3$ & 4). Since the results vary from patient to patient, we evaluate the results using aggregate and disaggregate information with different design configurations. First, we present disaggregate information in the form of cumulative frequency plots. Second, we present the aggregate information in scatter plots and tables. The results of the simulation model are presented in the subsequent sections.

5.1 Cumulative frequency plots for waiting time

The results in this section discuss the concept of '*equity*' using the '*waiting time*' metric. Such metrics have already been documented in Marsh and Shilling (1994). While a Lorenz curve may be a helpful tool for comparison, we choose a cumulative frequency plot which is a slightly modified version because of ease of comparison on the metric of interest. A cumulative frequency plot will help analyze the chosen metric for all the patients. An ideal model should have lower waiting times for most patients compared to other models. A better-performing model will have its cumulative frequency in the shape of 'Γ'. Any deviation from this shape indicates the poor performance of the model. In such plots, one thing to note is that the x-axis will have units normalized between 0 and 100. Therefore, we normalize the waiting time in all our analyses before plotting these graphs. Normalization is accomplished by dividing the individual waiting times of patients by the total waiting time of all the patients and then scaled to 100. The Y-axis represents the cumulative frequency of the number of patients.

Figure 3 clearly reveals the effect of flexibility in the choice of locational model. The patients' waiting time (equity) is influenced by the locational model, namely P-median, P-center, and P-center-beta. Specifically, for $P = 3$, we find no single model dominating the other. Further, in the 2-OPDOs scenario, 80 percent of patients have a waiting time less than a normalized waiting time of 20 units, and 17 percent of patients have a waiting time between 20 and 40 units. Thus, from Fig. 3, we can conclude that all three models perform similarly on the metric waiting time for a 2-OPDO scenario.

However, a similar analysis for the 3-OPDO scenario provides a different perspective. For a 3-OPDO scenario, the models exhibit a significant departure, with P-median and P-center-beta models exhibiting better performance for 80 percent of customers with a normalized waiting time of fewer than 20 units. However, the P-center model performs better for the remaining 15 percent of customers, where cumulative waiting times are more than 20 and up to 60. The performance of these models is similar when the 4-OPDO scenario is considered. Further, the models yield slightly different results, with P-median and P-center-beta performing well for most patients.

5.2 OPDOs, locational models, and equity-efficiency trade-off

Although insightful, the previous analysis does not demonstrate the effects of clinical (blood group) and non-clinical (Type of OPDO, Locational model) factors. Since the effect of these factors may be evident at an aggregate level, we carry out the aggregate waiting for time
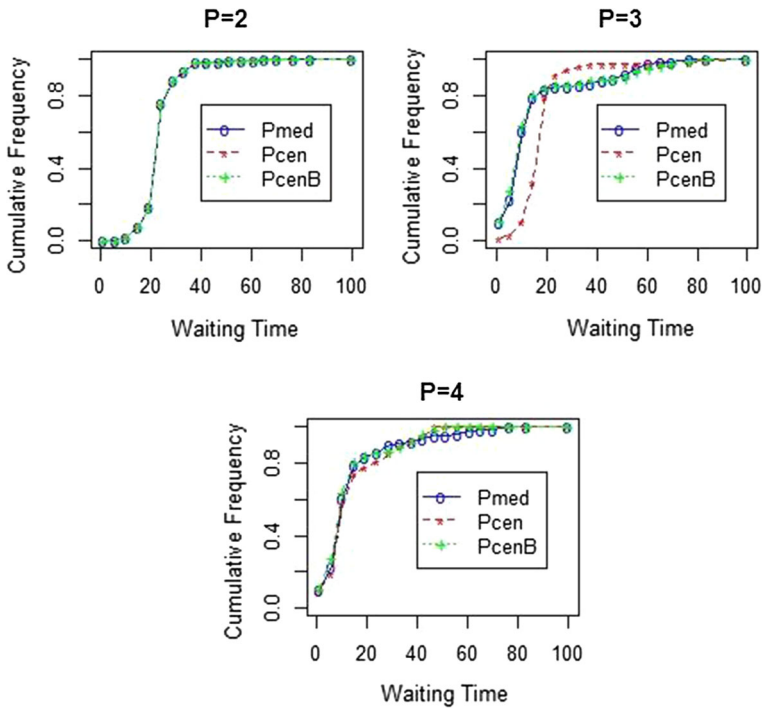
Fig. 3 Cumulative Frequency Plot and Waiting time—2, 3, 4 OPDOs

analysis across the following variables: Blood group, Type of OPDO (Dense/Sparse clusters), and the location model employed. Further, since aggregate analysis is considered, we use '*average waiting time*' to measure equity.

Figure 4 shows that the average waiting time exhibits dissimilarities across the blood groups and the number of OPDOs. Specifically, the current representative zonal structure of three OPDOs has a higher variance in the average waiting time across all the blood groups than in the other scenarios. Surprisingly, the variation is less for the rarest blood group AB than for prevalent blood group A. The universal blood group O shows a higher waiting time variation in the 3-OPDO cluster than the other two.

There is also dissimilarity between the dense and the sparse clusters. The sparse cluster exhibits a higher variance than the dense cluster for all the blood groups, which may be attributed to the arrival patterns between the dense and sparse clusters. Organ arrivals are generally more frequent in a dense cluster than in a sparse cluster due to higher cadaver donations resulting in a higher supply of organs in these regions.

The influence of the location choice on the average waiting time yields a similar result (see Fig. 5). The waiting times differ significantly between the P-center and P-center-beta models and the P-median models. Specifically, the P-center model seems to have a higher waiting time than the other two models for blood group A. The waiting time for this blood group also exhibits higher variance. All the locational models exhibit a lower average waiting time for the rarest blood group, AB, which could be because of the infrequent donor arrivals for this blood group coupled with a lower number of registered patients on the waitlist for this blood group.
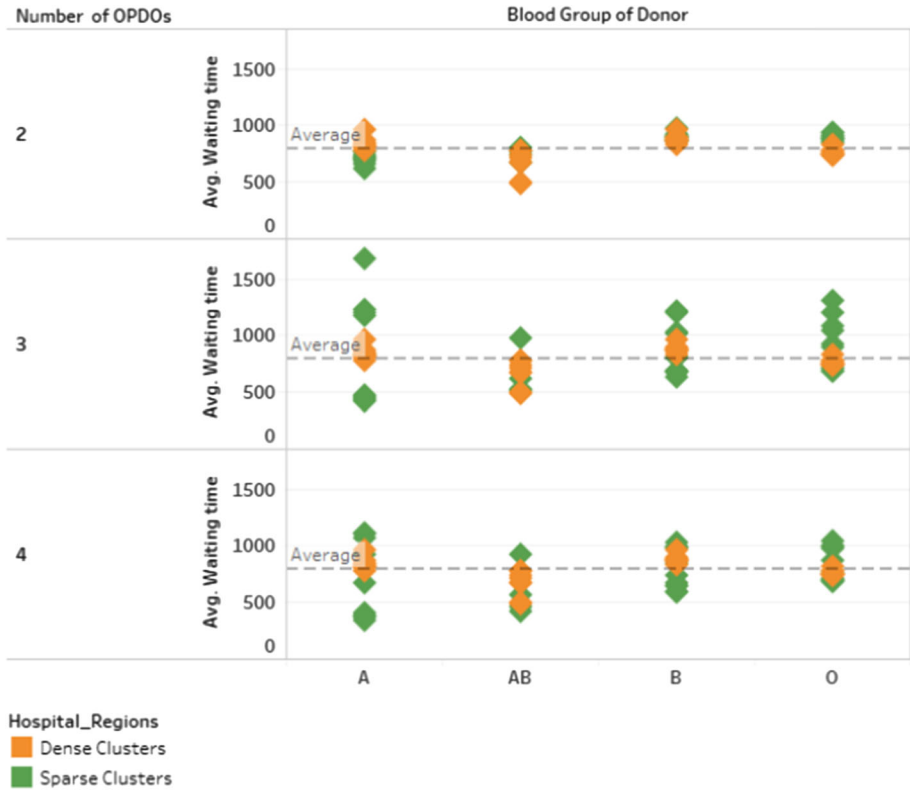
Fig. 4 Average waiting time based on the number of OPDOs

The more common blood group O shows a higher waiting time in all the models. Further, these waiting times differ significantly between dense and sparse OPDOs. In other words, variation in waiting times for dense clusters seems to be considerably less than that for sparse clusters. As discussed earlier, this could be attributed to more donations than the sparse cluster.

5.3 Unallocated organs and equity

The encouraging results from the previous section motivated us to study another aspect of organ allocation, namely the 'number of unallocated organs' resulting from applying a location-allocation model in this section.

As mentioned earlier, organ arrivals remain the same across all models, implying the donor organs arrive simultaneously for all location models. However, since different location models result in different designated OPDOs and associated TC affiliations, we hypothesize that the number of unallocated organs after completing the simulation will differ in each model.

Thus, we undertake a simple analysis of the unallocated organs in each scenario across different location models and the number of OPDOs. Table 7 shows that location models identified as efficient in terms of distance are found to be the most inequitable, in that order. In other words, the most efficient P-median model performs the worst. The least efficient
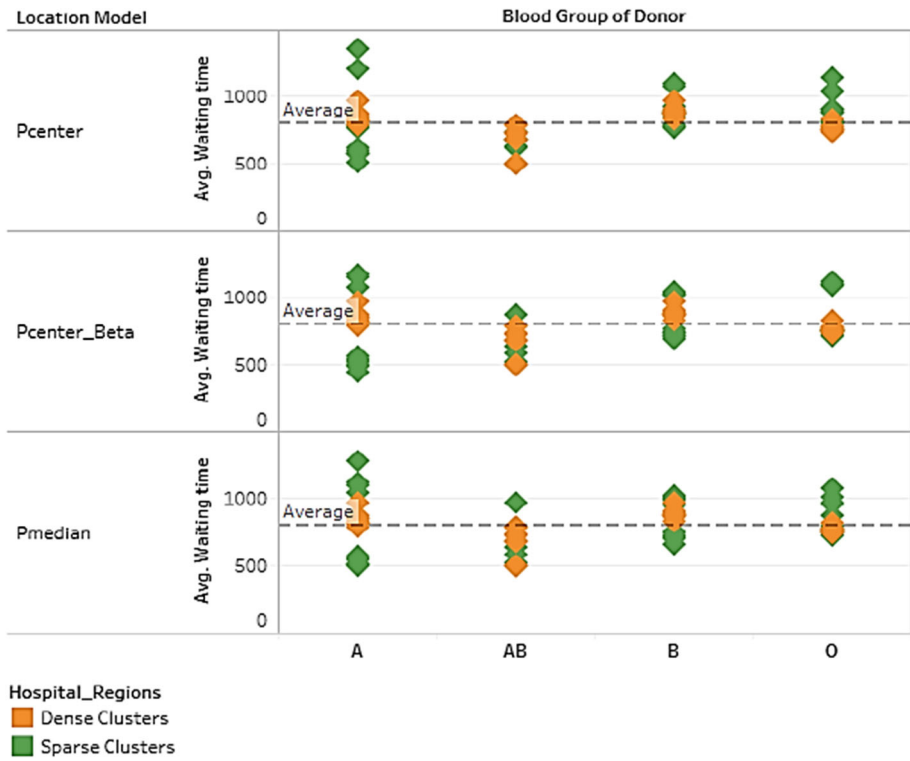
Fig. 5 Average waiting time based on the location models

Table 7 Number of Unallocated organs in each scenario

Location model	OPDO = 2	OPDO = 3	OPDO = 4	Total unallocated organs
P-center	0	0	25 (A = 17, B = 8)	25
P-median	0	33 (A = 22, B = 11)	66 (O = 28, A = 22, B = 16)	99
P-center-beta	0	43 (O = 5, A = 24, B = 14)	43 (O = 5, A = 24, B = 14)	86
Total Unallocated organs	0	76	134	

P-center model resulted in the minimum number of unallocated organs. Commensurate with the observation from the previous section, the number of unallocated organs is high for blood group A, followed by B.

5.4 Findings from the study

Compared to Fillippi et al. (2017) findings, this study confirms that these locational models are sensitive to changes in *P*. The study acknowledges that all models' computational time is reasonable, ranging from 5 to 15 min. Further, our results confirm the extant literature observations that the P-median model performs better in the mean distance metric. We augment this finding that the P-center model is better in terms of CV and maximum distance metric, while the performance of the P-center-beta model lies in between the two. Hence, if the objective of the locational model is minimizing the worst-case coverage distance, P-center is a good choice.

However, the same may not be said about the metric waiting time. We find that no single locational model dominates the other models in waiting time from our observation, except for the scenario $P = 3$, where each model dominates for only a certain percentage of the population. This shows that locational model selection can result in fluctuating equity in the organ transplantation network.

In relation to waitlist size, we observe the total waitlist to be minimum for lower values of P, and with increasing values of P, the number on the total waitlist increases. Waitlist size is influenced by the locational model employed and the number of OPDOs, and this effect is more pronounced in the case of $P = 4$. This contrasts with the arguments of Beliën et al. (2013), where the total waitlist decreases with more OPDOs. This could be the result of the local primacy allocation procedure, which is currently the case with that of the allocation rules. A more dynamic allocation process with organs allocated to neighboring zones or states may alleviate this problem.

Further, the study results are different in the number of OPDOs to open compared to Belien et al. (2013). Based on their mathematical model, the authors advocate opening lesser centers when considering the total waiting time of the organ outside the body. However, based on our analysis, the authors believe that the behavior of equity fluctuates when the total waiting time of recipients is the variable of interest. Unlike Belien et al. (2013), where the total waitlist number is influenced by non-clinical factors such as distance, our study noted that the total waitlist number is influenced by clinical and non-clinical factors such as blood group, type of OPDO, and locational model employed.

Furthermore, equity is influenced by the rarity of the blood group. For instance, the rare blood group such as AB exhibits a clear advantage with lower overall waiting times than the more prevalent O-type blood group. This observation is valid across all the location models. The other interesting result is the derived metric on the number of unallocated organs. The most efficient P-median model performs the worst with the most unallocated organs for a similar arrival distribution. On the contrary, the least efficient P-center model is the most equitable in the chain for this metric.

6 Managerial implications

The study contributes to the extant literature in multiple ways. First, it investigates the consequences of locational choices on the trade-off between equity and efficiency in kidney transplantation. The findings validate the fundamental proposition of equity and efficiency trade-off in OPDO location and organ allocation in complex humanitarian supply chains. Specifically, these models affirm the role attributed to patient equity in the locational choice

models. Second, although our results on the metric mean distance align with existing literature (i.e., using different locational models), these results differ when considering the worst-case distance and CV. The P-center model performs better in these metrics.

Besides, our study characterizes the role of patient 'waiting time,' which depends mainly on the selected locational model, number of chosen facilities, their type, and blood group. Third, our simulation results suggest that no single model dominates on either 'equity' or 'efficiency,' and the equity is sensitive to changes in values of P. This is one of the significant revelations from this study. Fourth, our study acknowledges the role of cluster density in the allocation, a significant contribution of our study. The study supports the inference that dense clusters exhibit a homogenous waiting time across blood groups compared to the sparse groups from our experiments. The results of the case study point to the need for more deliberations on organ recovery mechanisms and minimizing organ wastage in the sparse clusters.

These overall deliberations have a broader implication for policymakers. First, considering the patient equity in mind, real-life OPDOs' location-decision should involve a detailed study of locational models because of their individual varying effects. Second, equity and efficiency results strongly depend on the locational models employed. The most efficient model is the P-median model. However, this behavior is in-conclusive in the waiting time distribution. The most efficient P-median model is the 'inequitable' model in the 'waiting time' metric.

Also, in a specific scenario: 3-OPDOs significantly affect the distribution of waiting times. This input would help the planners to design and prioritize their processes. Third, blood group and cluster density also impact waiting time distribution. Fourth, the waitlist number allocated is influenced by OPDOs location, as evident from the number of unallocated organs. This is a key input to operational planning and provides directions to policymakers for their locational choice decision-making. The deliberations support the idea of combining the models for location-choice decisions.

One of the existing allocation criteria, namely 'local primacy,' possibly leads to many unallocated organs, especially when the number of OPDOs increases. Managers may need to investigate this under dynamic allocation criteria. Regarding the number of OPDOs, the current zonal structure of 3-OPDOs also represents the highest variance in the patient's waiting time, which significantly bears organ equity. Therefore, the policymakers may look to re-engineer the existing kidney transplant network configuration. Finally, the higher waiting times for sparse clusters point toward policymakers' need to focus on procuring kidneys effectively in these locations and reducing organ wastages.

7 Conclusion, limitations, and future scope

The paper has utilized a K-sum optimization approach to study location decisions and the consequent long-term impact on the equity and efficiency of a kidney transplant network in a developing economy. Locational choices were made using this model, and the chosen facilities were designated OPDOs for analysis. An allocation policy was devised close to the existing policy, followed by the government entity, TRANSTAN. The procedure was simulated based on the historical organ arrival data from a public report and matched with recipients from an existing waiting list listed on the same website. We show a trade-off between efficiency and equity for the selected case study. i.e., the most efficient model in terms of efficiency need not be the most equitable.

The literature shows that when the model considers only equity (waiting time), centralization of facilities may be a better option (Beliën et al., 2013). Our experiments seem inconclusive because findings indicate that changing the number of facilities during the locational decision has a fluctuating impact on equity (waiting time). This behavior suggests the multi-modal nature of the equity-efficiency trade-off function earlier pointed out by Cho (1998). Future experiments are needed to confirm this pattern.

The current COVID-19 crisis has a significant impact on organ arrivals, which is not captured as-is in our simulation model. However, our simulation study can be modified to reflect the current organ arrival patterns and patient characteristics on the waitlist. Frequent lockdowns since March 2020 have taken a toll on the number of cadaver donations. Because of the continual lockdowns in the region, the TRANSTAN had briefly restricted kidney transplantation in TC. The state has seen an unprecedented reduction in the number of organs donated and the number of transplants conducted during this period. The number of kidneys donated in 2020 is 91 compared to 212 in 2019. An increased demand–supply mismatch coupled with such decisions will significantly impact critical patients needing dialysis and transplants. Such choices and uncertainties are already reflected in the all-time higher numbers on the active waitlist (TRANSTAN). The current active number of waitlist patients has touched an all-time high of 6000. This demand–supply imbalance significantly increases the waiting time to receive such organs and increases the risk of mortality due to the contraction of deadly viruses. This leads to a silent physical and mental crisis for the patients.

Our study is limited to the blood group as the only clinical factor in the allocation policy. Future studies can include more clinical factors such as graft quality and co-morbid conditions that are realistic and effective for developing allocation policies. Further, our study represents CIT indirectly as distance in the locational model. While this allows indirect characterization of this critical factor, this may result in a design with conservative assignment during the locational stage. The inclusion of CIT directly in the model may provide a more accurate design configuration with optimal utilization of travel times.

Alternatively, to address the increasing demand–supply mismatch, the policymakers can consider employing simulation studies to study the effect of location and allocation policies. The advantages of such studies are the ability to arrive at decisions quickly and effectively. Also, the current model is restrictive because of the assumption of organ arrivals being spread throughout the year, although arrivals are generated based on past data. More studies require exploration of the role of equity under irregular or seasonal organ arrivals. The study also ignores the perception of OPDOs in terms of fairness and transparency of the patients. Further investigations may address this dimension that can offer key inputs to standard procedures.

Appendix

See Tables 8, 9 and 10.

Table 8 Deceased donors from the Annual Report 2015 (Used for Forecasting Donor arrivals)

Month	Year	Donors
April	2014	8
May	2014	7
June	2014	8
July	2014	16
August	2014	12
September	2014	14
October	2014	13
November	2014	14
December	2014	14
January	2015	16
February	2015	19
March	2015	14

Table 9 Distribution of kidney transplants based on blood group

Blood type	No. of transplants
O	110
A	62
B	84
AB	19

Table 10 The number of donations from each hospital

TC	Donations
Apollo TC, Chennai	45
Global Hospital, Chennai	30
Rajiv Gandhi Government Central Hospital, Chennai	21
Stanley Government Medical College Hospital, Chennai	20
CMC Vellore	19
Fortis Malar, Chennai	6
Sri Ramachandra, Chennai,	10
MIOT TC, Chennai	30
Kamatchi Hospital, Chennai	2
Vijaya Hospital, Chennai	2
Kovai Medical Center and Hospital	20
KG TC, Coimbatore	18
Sri Abirami Hospital, Coimbatore	2
G Kuppuswamy Naidu Memorial Hospital, Coimbatore	26
Kovai Medical Specialty Hospital, Coimbatore	4

Table 10 (continued)

TC	Donations
Salem Gopi Hospital	4
Meenakshi Mission, Madurai	2
KMC, Trichy	2
Frontline TC, Trichy,	8
Cethar TC, Trichy	2
Meenakshi Hospital, Thanjavur	2

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