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Research Article

Perspective on Macroscale Complexity in the National Transplant System

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We present a perspective of the national transplant program based on organizational theory and complexity theory, framing the system's allocation of donor organs as an interorganizational directed multiplex of agents with diverse belief formation in a cooperative-competitive environment. Simulation and analysis of this macroscale complexity may help explain known behavioural variations across member organizations. However, the transplant community still relies on system-scale simulations since effective macroscale methodologies are not well established. Therefore, we offer this perspective of the national transplant program as a means to stimulate new methods that capture macroscale impacts of policy development for deceased donor organ allocation.

1. Introduction

The Organ Procurement and Transplantation Network (OPTN) is a public-private partnership that governs all solid organ transplants in the United States. Solid organ transplants include kidney, liver, heart, lung, pancreas, intestines, and vascularized composite allograft (VCA, e.g., hands). While some solid organs, such as a kidney, can be donated from a healthy living donor, most organs are supplied from deceased donors. In order to receive a deceased donor organ, potential transplant recipients, known as transplant candidates, must be added to the national waitlist. Approximately one hundred and six thousand individuals currently await an organ transplant on the national waitlist. While nearly forty thousand transplants across both living and deceased donor types were performed in recent years, roughly sixty thousand new waitlist individuals are added each year (https://optn.transplant.hrsa.gov/data/view-data-reports/national-data/).

Given that demand for donor organs outpaces supply, a key function of the OPTN is to determine equitable organ allocation policy that minimizes unutilized organs. In 1984, Congress passed a law to create the OPTN (https://www.organdonor.gov/about-us/legislation-policy), which stipulated that a private, nonprofit organization should manage the allocation of deceased donor organs. In the year 2000, the final rule was created (https://optn.transplant.hrsa.gov/governance/about-the-optn/final-rule/), which provided the OPTN a regulatory framework for policy making pertaining to organ allocation. Today, the United Network for Organ Sharing (UNOS) (https://unos.org/) is the contractor responsible for operating the OPTN, which includes facilitating policy development through its board, topic-specific committees, and community forums (https://optn.transplant.hrsa.gov/governance/policy-development/).

Each solid organ has allocation policies that are developed, maintained, and evaluated by a committee of national experts. Committees include transplant domain expertise in medicine, surgery, logistics, recovery, and administration. In order to change national allocation policy, these committees must first gather supporting evidence, typically by studying historical

OPTN data to show inequities or inefficiencies. Based on these results, committees begin developing potential changes as a policy proposal. Once a policy proposal is well-defined, confirmatory simulations are performed by the Scientific Registry of Transplant Recipients (SRTR) (https://www.srtr.org/). Simulation results combined with the evidence manifested in prior stages are then shared in the final presentation of a policy change proposal. The public is then given opportunity to review the evidence in a public comment period. Critical feedback from public comment can necessitate further iteration in evidence gathering, policy development, and simulations. Finally, once the Governance Committee agrees that feedback has been sufficiently addressed, the change is presented to the OPTN Board of Directors. If approved, the policy change is implemented by the OPTN contractor.

The complexity of the OPTN coupled with its critical service has made simulation modelling a key step in policy development. Pioneering work implemented the UNOS Liver Allocation Model (ULAM) [1], an event driven model later used to develop a score for liver allocation [2]. Additional simulation efforts for kidney allocation soon followed [3], as well as further development of liver-specific models [4, 5]. The SRTR later presented three separate simulated allocation models, or SAMs, for studying allocation in liver (LSAM), thoracic (TSAM), and kidney-pancreas (KPSAM) [6]. Simulation efforts have continued, with focus on decoupling system simulation into modules [7, 8] and understanding small-scale processes [9, 10].

As facilitated by the regulatory framework, the OPTN consists of many member organizations that enable the allocation of deceased donor organs to those in need. While existing simulation models have demonstrated remarkable ability to capture system level effects of policy change, the macrolevel and mesolevel analysis of policies, interventions, and predictions of its future behaviour have been confounded by its complex nature. This is of particular importance given that the system seeks to maximize organ utilization by exploiting heterogeneous agent behaviour without increasing disparities within the system (https://optn.transplant.hrsa.gov/resources/by-organ/kidney-pancreas/kidney-accelerated-placement/).

In this perspective, we present an interorganization model for organ allocation in the OPTN using organizational network theory and complexity theory. We continue by highlighting how the OPTN is subject to divergent beliefs from several sources and that this heterogeneity is a key enabler of the OPTN's flexibility. We conclude with recognition that several fields—complexity science, organizational science, computer science, and others—have potential approaches and concepts for better macroscale models, but methodology remains unclear. These challenges are not unique to the OPTN and we expect improved methods through interdisciplinary collaboration that will benefit other domains of complex interorganizational behaviour analysis.

2. Network Operation and Structure

In this section, we describe the macroscale structure of the OPTN and propose a conceptual model of this structure based on existing organizational and complexity theory.

2.1. Organ Allocation at the Macroscale. The OPTN operates as a regulated market in which organs are offered to waitlisted candidates based on enacted organ allocation policy (https://optn.transplant.hrsa.gov/media/eavh5bf3/optn_policies.pdf). Each Organ Procurement Organization (OPO) has sole authority over a region of member donor hospitals. Within their region, OPOs are responsible for identifying potential donors and procuring organs for use by a transplant hospital. When a deceased donor becomes available, the OPO instantiates an "ephemeral market" process that first orders compatible candidates based on allocation policy. The OPO proceeds through the ordered list of potential recipients, offering the organ for transplant to the individual's transplant hospital. Decision makers at the transplant hospital must adjudicate the offer based on many factors, such as prospects for survival and the potential for better offers in the future [11]. Furthermore, given the time-sensitive nature of the transaction, OPOs and transplant hospitals often discuss and coordinate to finalize a decision quickly. The approximate sequence of decisions coordinated by OPOs and transplant hospitals is shown in Figure 1.

Transporting a viable organ for transplant presents many logistical challenges. For this reason, OPTN policy prioritizes offering organs to transplant hospitals geographically closer to procurement. However, offers within the closest geographical region can be exhausted without an acceptor. When this occurs, the OPO can optionally escalate the allocation to UNOS's Organ Center (OC) for assistance, a 24-hour call center required by policy that is staffed by organ placement specialists who help find an acceptor anywhere in the nation. This includes contacting transplant hospitals far outside the procuring OPO's jurisdiction. Should a transplant hospital accept the organ at this point, coordination is often required between the original procuring OPO, the accepting transplant hospital, and the transport services of the acceptor's OPO. The OC often helps to facilitate this coordination as well.

Additional information-sharing processes exist within the OPTN, such as the use of tissue typing and histology labs for determining compatibility. Some processes may produce information that is required by policy, such as a virtual cross-match, but these may also produce additional information not required by policy, such as the results of a biopsy. This flexibility allows for discovery within the network, but collection of these additional data is not standardized, making analysis difficult. These additional processes increase small-scale complexity within the OPTN, but they are outside the scope of this paper's focus.

2.2. Orchestrated Emergence within the OPTN. Interorganizational network theory and complex network theory both provide models applicable to the study of complexity within the OPTN. Traditional network-based models of organizations describe a relative arrangement of agents predicated on the rules of reciprocal exchange [12]. More recent organizational network theory expands this general definition to recognize two distinct types of networked organizations. Borgatti and Halgin describe a first

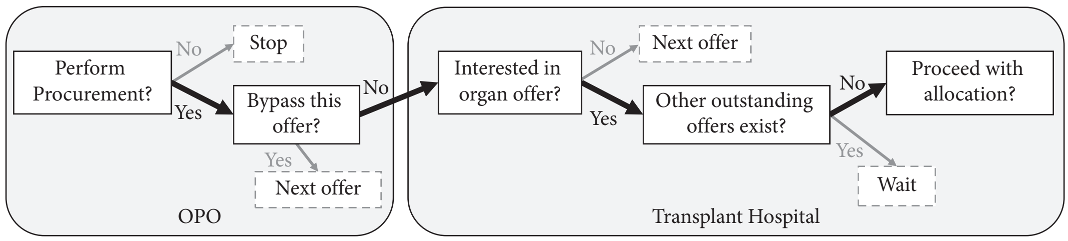

Figure 1: Simplified decision tree of OPOs and transplant hospitals during organ allocation. Allocation begins with the decision to perform procurement of a deceased donor. The term "procurement" in this illustration is abstract and represents the decision to work with hospitals on attempting to allocate the donor's organs to candidates. OPOs may decide to bypass certain offers, but must document the reason for the exception. Once a transplant hospital is notified, they can either express interest in the offer or decline it outright. Only when no other preceding offers exist does a transplant hospital become the primary responder. Ultimately, the decision to perform procurement and transport donor organs to the accepting facility lies with the OPO.

type of network governed by formal rules and a second type of network that is transactional, governed by the flow of resources [13]. However, complexity researchers have recognized "orchestrated emergence" in which a central authority sets some formal rules, but individual organizations have agency over their operations within the constraints of the authority's rules [14]. This type of network readily gives rise to a complex network in which agents can cooperate and compete simultaneously [15, 16].

We conceptualize organ allocation within the OPTN as resource flows within a directed multiplex of organizations. While a central authority sets policy that governs organ allocation, member organizations retain broad agency in decision-making and propagation of discoveries. In this interorganizational network, OPOs make organ offers to transplant hospitals within the constraints and rules established by the central authority. Additionally, the OC aids in national-scale allocation coordination and is represented as a bridging organization with weak ties to all members of the OPTN. We omit these weak ties from Figure 2 for visual clarity and instead illustrate how the OC augments an OPO's reach during allocation.

Conceptualizing the OPTN as directed multiplex aids in framing the complexity and scale of the national transplant system. This complexity is necessary to allow the OPTN to adapt to the wide variety of organ offers and the candidates who receive them. For example, medical science can evidence compatibility constraints that must be followed—e.g., compatible blood types—but no governing body can plan for the myriad of other challenges, such as inclement weather or the nuanced medical needs of a recipient.

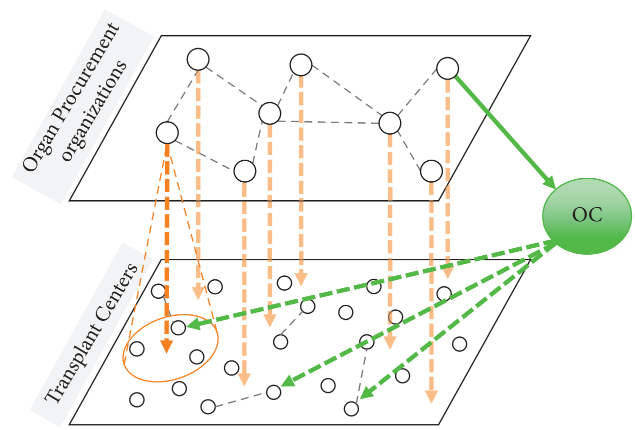

Figure 2: Directed multiplex structure of information sharing within the OPTN during allocation. Each OPO (top layer) has authority in a geographical region that encapsulates several transplant hospitals (bottom layer). The two spatial dimensions of the layers correspond to geographical relationships, since physical distance influences organizational ties and authority. An ellipse covering multiple hospitals illustrates OPOs' one-to-many relationship with transplant hospitals. Physically adjacent OPOs typically have emergent links arising from the geographic locality preference of policy. Transplant hospitals may develop links through personnel exchanges from recruitment, attrition, and residents who become physicians at the other transplant hospitals. The Organ Center (OC) facilitates bridging between disparate organizations during allocation. Note that the number of nodes illustrated in each layer is smaller than the actual system and is only to convey that transplant hospitals outnumber OPOs.

3. Divergent Beliefs across Organizations

Timely allocation decisions require evaluation of the context, including available information such as medical factors and transportation availability, while simultaneously considering the larger cooperative-competitive interorganizational landscape. The broad agency afforded to transplant hospitals and OPOs helps the OPTN to adapt to these changing complexities. However, this flexibility also enables a variety of beliefs to form across the network.

Several studies have evidenced variability in offer acceptance practices during allocation. Risk-adjusted models have shown high variability in acceptance of liver offers, with some hospitals accepting 15.7% and others accepting 58.1% of offers to their highest priority candidates [17]. Separate work has produced similar results for heart candidates [18]. Hospitals also vary in lung offer acceptance, ranging from 9% to 67% risk-adjusted acceptance for candidates offered first [19]. For heart allocation, significant variation was found, including acceptance practices relying on covariates that are not correlated with post-transplant mortality [20]. Kidney transplant probability has also been shown to vary widely, even within the same region, and that this is correlated with offer acceptance patterns [21]. Controlled behavioural research of kidney offer acceptance practices also demonstrated acceptance rates ranging from 11% to 95% across medical doctors [22]. Other work has shown how monitoring and enforcement also causes fluctuations in practice [23, 24]. OPOs must also make critical decisions, including anticipating the decision needs of responding hospitals. Recent research surveying the practice of 86% of OPOs showed that the decision to biopsy a kidney in support of allocation varies. Most OPOs reported formal criteria, but a significant amount will biopsy a kidney at the request of a hospital. The authors report large differences in the criteria, technique, and biopsy interpretation [25].

We illustrate in Figure 3 the key components and relationships that influence the formation of beliefs within the OPTN. The following sections consider two types of influences separately, stochastic processes and the cooperative-competitive environment, and how both can give rise to apparent divergence of beliefs during observational analysis. We believe that improved macroscale representation within OPTN simulation studies may help the community better understand and account for variations in practice.

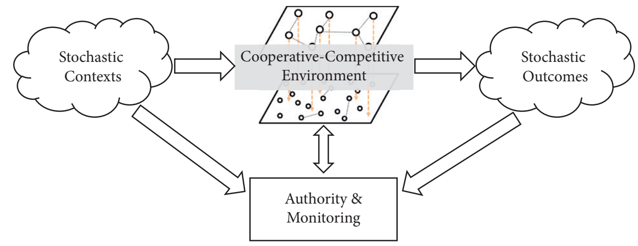

Figure 3: Information and behavioural feedback loops within the OPTN. Both stochastic processes and their own cooperative-competitive environment govern the interorganizational multiplex.

3.1. Stochastic Processes. Transplant hospitals and OPOs within the OPTN are subject to wide variation in experience from stochastic processes. We consider any system that has unpredictable behaviour at the small scale, while still being informative in aggregate as stochastic. For example, a transplant hospital in a large city is likely to field far more offers than transplant programs in smaller communities. Naturally, candidate populations and medical needs will also vary stochastically over time and geography [26, 27]. Even transportation options, such as number of direct flights or highway access, may influence how a transplant program reasons about allocation decisions. Similarly, OPOs must contend with both transportation from donor hospitals as well as delivery to the accepting transplant hospital [28]. In addition, deceased donor availability and transplant recipient outcomes are themselves stochastic—distributions and models can inform decisions—but random or unobservable aspects reduce the reliability of any attempt at precise predictions.

The challenge of stochastic processes is not unique to the OPTN, but its presence in a highly flexible system aids in the formation of divergent beliefs. Even in theoretical modelling analysis, cases where agents weighted their own experiences slightly higher than others resulted in polarization of beliefs. Removing biased weighting and instead penalizing model complexity to simulate bounded rationality still results in belief polarization among agents [29]. These results suggest that divergent beliefs may be arrived at with little or no preexisting biases; they are instead emergent within a stochastic system.

The challenge of understanding how to make decisions effectively in an environment can also be framed as a reinforcement learning (RL) problem. In an RL problem, an agent must learn through trial and error within a dynamic environment [30]. However, in the domain of healthcare, RL problems and their proposed solutions face many challenges in practice [31, 32]. Continuous control and healthcare face many similar issues: delay in reward relative to system state change, difficult-to-observe decision restrictions, plentiful historic data with unclear methods to utilize, and a need for explainable methods [32]. These issues are likely to translate into offline simulation of a macroscale representation of a system. Simulating the OPTN's macroscale behaviour may find success through formulation as an RL problem, but cross-disciplinary efforts must work to integrate the concepts in a way that remains applicable.

3.2. Cooperative-Competitive Environment. When allocating deceased donor organs, options are limited, but variation is high. OPOs must decide whether to procure organs from a deceased donor, while transplant hospitals must decide whether the organ is right for their candidate. OPOs are encouraged through policy to procure the organ and make it available [33], but at the risk that it is not accepted by any transplant hospital, wasting resources, and potentially incurring surgical costs. Separately, transplant hospitals' outcomes are also monitored [34], including their willingness to accept donor organs in comparison to all other transplant hospitals. The details of these incentives are subject to change with policy, and their influence on the interorganizational multiplex is difficult to comprehend with standard analysis.

We view the OPTN as having established a cooperative-competitive environment with these incentives. Sometimes called "coopetition," cooperative-competitive systems are more recent and typically seen in industrial sectors [35]. Within the OPTN, we assume all organizations operate in good faith and cooperate towards a shared goal of saving lives through transplantation. However, transplant hospitals must consider organ availability and the likelihood that an organ will be accepted before it reaches their candidate. They must also consider the acceptance practices of other transplant hospitals, being sure not to be more risk-averse than necessary while also not degrading their patient outcomes with risk-tolerant transplants.

Both OPOs and transplant hospitals are private organizations; their continued existence is predicated on their success. Poor performing OPOs may be subsumed by a nearby, more successful OPO. Similarly, transplant hospitals may be unsuccessful in their management of operations and decide to close. Though each registration incurs cost, patients can opt to register at any number of transplant hospitals anywhere in the nation. This additional element to the competitive landscape means a transplant hospital may find success with local patients or national ones, developing niches of expertise to appeal to the population.

4. Conclusion

The OPTN will continue to face a changing medical, technological, and behavioural landscape. Supporting agencies will continue to explore ways to collapse unnecessary complexity, simplify decision-making, and increase transplants (https://techcrunch.com/2021/09/22/how-technology-is-transforming-organ-procurement/). Advances in technology allow streamlined transportation planning (https://unos.org/wp-content/uploads/1-page-Travel-App.pdf), with traversal monitored for unexpected events and precise arrival times (https://unos.org/solutions/organ-tracking/ and https://gomedigo.io/). Current OPTN simulation methodologies will be challenged to understand how contemporary innovations and practices influence organizational behaviour.

We suggest research on methods for modelling belief formation from observational data and the subsequent application and adjustment of those beliefs from a simulated experience. Successful methods should validate past experiences of divergence in decision-making. The competitive-cooperative environment's influence is also subject to varied contexts and belief formation. Preliminary efforts should prioritize parsimonious techniques that make explainable adjustments to behaviour based on the simulation of deterministic monitoring processes.

Simulation results, especially macroscale results, must be interpretable to help validate with organizational subject matter experts. Interpretable results allow experts to reason about a simulation's predictions rather than rely solely on historic validation, improving trust and reliability in the simulations forcasts. We suggest creating a conversation surrounding simulation results and giving close consideration to the assumptions, limitations, and findings. Consideration of how to structure these conversations and communicate simulation methodologies will benefit interested communities. This is critical during public comment of policy proposals supported by simulation analysis.

Data relating to decisions and organizational ties may not exist or may simply be unreliable. Therefore, the details of organizational ties and information sharing may not be robust enough to support modelling macroscale behaviour. In this case, strong evidence from the simulation community could support requiring the collection of representative data. However, these changes take time to implement and to amass a mature enough database for retrospective research. Instead, researchers should consider supplementing with synthetic data or work to estimate the relationships through modelling of proxy features.

Clearly, the OPTN and its agents adapt, and so must its governing policy. Sciences and experiences shape policy within the OPTN, but understanding the potential impact of a policy change on the macroscale organizations lies at the intersection of many disciplines related to complexity science. We believe that improved representation of organization-level behaviour will yield insight and better anticipate impacts of policy changes, technological advances, and development of medical practices.

Data Availability

No data were used to support the findings of the study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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