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REVIEW ARTICLE

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A literature review of perishable medical resource management

Abstract In recent decades, healthcare providers have faced mounting pressure to effectively manage highly perishable and limited medical resources. This article offers a comprehensive review of supply chain management pertaining to such resources, which include transplantable organs and healthcare products. The review encompasses 93 publications from 1990 to 2022, illustrating a discernible upward trajectory in annual publications. The surveyed literature is categorized into three levels: Strategic, tactical, and operational. Key problem attributes and methodologies are analyzed through the assessment of pertinent publications for each problem level. Furthermore, research on service innovation, decision analytics, and supply chain resilience elucidates potential areas for future research.

Keywords perishable medical resources, organ transplant, healthcare products, decision analytics, operations management

1 Introduction

Perishable medical resources include medical supplies and products with a limited shelf life that are susceptible to deterioration or spoilage. In recent decades, healthcare providers have faced shortages of such resources, particularly donated organs, as well as healthcare products such as platelets, cells, and drugs (Ayer et al., 2019; Wang et al., 2022). The limited availability of donated organs is the primary cause of protracted waiting times, resulting in an elevated risk of mortality among candidates. In 2020, the International Organ Donation and Transplantation Registry reported an excess of 345400 patients awaiting organ transplants. Unfortunately, more than 23100 patients listed for kidney transplants succumbed before finding a suitable organ match (Aubert et al., 2019). The burgeoning demand further exacerbates the shortage of healthcare products. For instance, in the US, platelet transfusions increased by 11.9% from 2008 to 2011 (Stroncek and Rebulla, 2007). This predicament is especially pronounced in nations with an aging population, where the supply of blood products often dwindles.

In addition to dire scarcity, the preservation time of medical resources has emerged as another significant concern owing to their perishable nature. Cold ischemia time denotes the duration between organ procurement and transplantation, approximating the preservation time of the donated organs. Hearts and lungs exhibit a cold ischemia time of approximately four hours, whereas livers and kidneys can endure for approximately 24 and 48 hours, respectively. In contrast, the preservation time of perishable healthcare products varies according to specific items, ranging from several days to a few weeks. For example, platelets and red blood cells maintain their quality for approximately one week and 6 weeks, respectively, following collection from donors (Abouee-Mehrizi et al., 2022). The limited preservation time of these donated organs and healthcare products inevitably diminishes their utilization rates, resulting in considerable operational inefficiency and wastage. In the US, nearly 80% of donated hearts[1)] have been discarded in the last 32 years, and 12.8% of produced platelets[2)] have exceeded their shelf life. Consequently, the squandering of medical resources exerts a substantial adverse effect on both the economy and public health.

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[1)] This data was reported by the US United Network for Organ Sharing (UNOS) in 2021.
[2)] This data was reported by the US Department of Health and Human Services in 2011.

In this study, we exclusively examine papers on supply chain management related to perishable medical resources, including transplantable organs, blood and blood products, and drugs. The review identified 93 published journal articles, excluding dissertations/theses, working papers, and conference proceedings from consideration. As depicted in Fig. 1, research on perishable medical resources gained momentum approximately from 2010, manifesting an upward trend in annual publications, with 18 publications in 2022. The identified papers were categorized into three levels of problems: Strategic, tactical, and operational (Fig. 2). To present the research trends, we provide a summary of research agendas (e.g., network design, resource allocation, and service innovations) for each problem level. The summarized research topics are related to specific types of medical resources. Additionally, to enhance our understanding of the research trends, we summarize the problem characteristics and modeling methodologies adopted in these research agendas. In doing so, we discuss our findings to highlight the following research gaps.

At the strategic level, infrastructure and logistics play critical roles in service network design. Existing studies optimize efficiency and fairness but overlook network disruptions. Moreover, these studies predominantly discuss conventional transportation modes, such as airplanes, leaving room for the exploration of new transportation technologies. When enhancing service networks, there is insufficient emphasis on ensuring system stability, particularly during transplant system reconfiguration. Regarding modeling methodologies, mathematical programs with tractable formulations prevail.

At the tactical level, demand constitutes a major source of uncertainty, with limited attention given to risk-associated objectives. Few studies have integrated resource allocation with mechanism design, which could facilitate

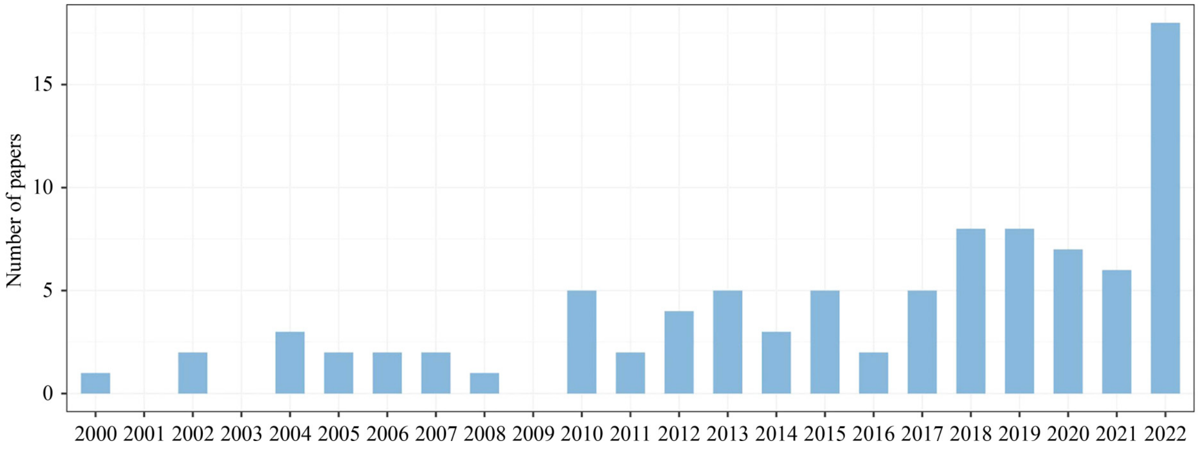
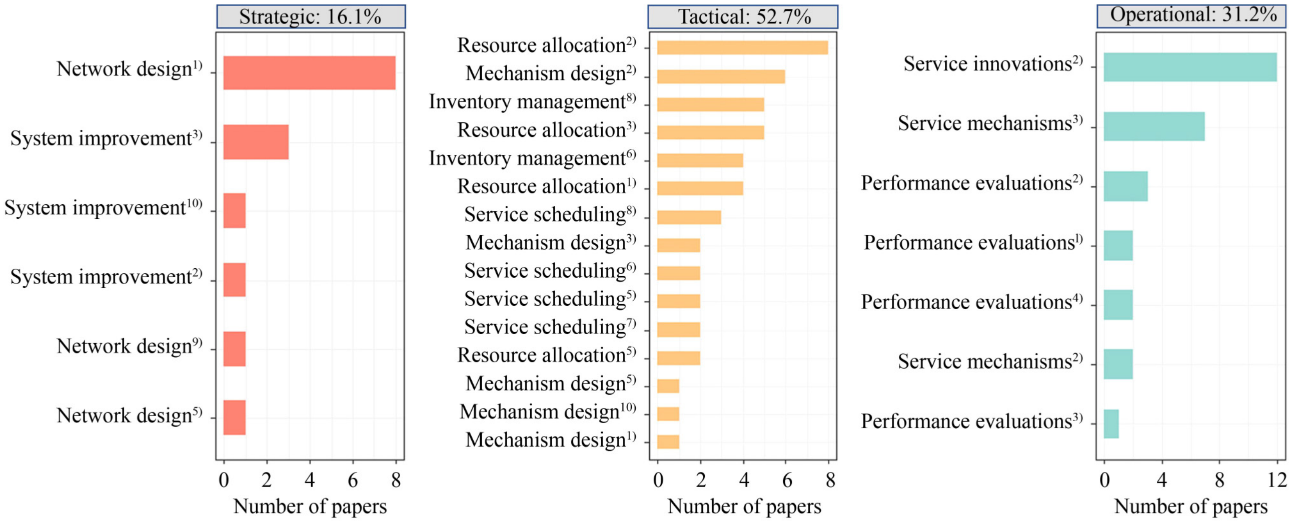


Fig. 1 Number of publications by year (2000–2022).



Notes: 1): organs; 2): kidney; 3): liver; 4): lung; 5): blood; 6): blood products; 7): cryo; 8): platelet; 9): cell; 10): drug.

Fig. 2 Research streams of perishable medical resource management.

further exploration of supplier behaviors (i.e., organ donor behaviors). Similarly, several studies combined service scheduling and inventory management. With the acquisition of more historical data, data-driven decision-making approaches (e.g., joint prediction and optimization) have the potential to find more applications.

At the operational level, a service is delivered at the individual level with real-time responses. Patients are stratified into several groups to receive personalized services. Their risk-averse attitudes drive them to opt for high-quality services. The primary focus is service innovation within organ exchange programs. The primary computational challenge is the “curse of dimensionality”, because the number of feasible exchanges can grow exponentially with the size of the exchange graphs. Compatibility between donors and recipients remains the principal source of uncertainty in organ exchange.

We observe a deficiency in research that highlights potential directions for future investigations (Fig. 3). First, we recognize the lack of research on service innovation. Disruptive technologies have revolutionized medical services in various ways. For example, Unmanned aerial vehicles (UAVs) can swiftly deliver medical resources to remote areas. However, along with their merits, disruptive technologies can also pose challenges, including financial investments and data security.

Second, we consider the scarcity of research in the realm of decision analytics. The current era of big data advocates data-driven decision-making, which has prompted the exploration of new approaches such as the end-to-end computational paradigm. Issues pertaining to behavior in decision analytics are gaining increasing attention. However, the intersection of these behavioral aspects with data-driven decision-making remains an underexplored yet promising avenue.

Third, we identify a deficiency in the research on supply chain resilience. Commonly adopted strategies, such as redundancy creation and emergent procurement, may prove inadequacy for cultivating resilience of perishable medical resources. Collaboration has emerged as a prominent approach involving various cooperative measures, such as information exchange, risk sharing, and system recovery.

The remainder of this paper follows the subsequent structure: Sections 2, 3, and 4 review strategic-, tactical-, and operational-level problems, respectively. In Section 5, we summarize our review, highlighting avenues for future research.

2 Strategic-level problems

Strategic-level problems constitute challenges that manifest at a high level and significantly influence long-term performance. Within the realm of perishable medical resource management, strategic-level problems typically revolve around strategic planning for service delivery within existing infrastructure (networks). In this review, we identified 15 papers that delved into strategic-level challenges. These studies have been categorized into two primary domains: Service network design and system efficiency enhancement. The former encompasses decisions related to facility location and resource allocation for the establishment of enduring service networks or systems, whereas the latter concentrates on decision-making processes aimed at refining the service efficiency of preexisting networks or systems.

Service network design. Most publications have primarily focused on infrastructure development within service networks. Bruni et al. (2006) focused on the establishment of nationwide transplant networks in Italy, specifically addressing the optimal partitioning of regions into organ procurement organizations (OPOs). Their objective function strives to minimize the overall travel distance while ensuring regional equity. Beliën et al. (2013) designed transplant networks to determine the optimal placement of transplant centers in Belgium. Their optimization model minimized the total travel time from donor hospitals to transplant centers. Case studies have revealed that reducing cold ischemia time can increase organ flow from donor hospitals to nearby transplant centers. Similarly, Salimian and Mousavi (2022a) constructed scenario-based transplant networks that considered the geographic locations of hospitals where organ procurement surgeries are performed. Their objective function aims to minimize organ delivery time while

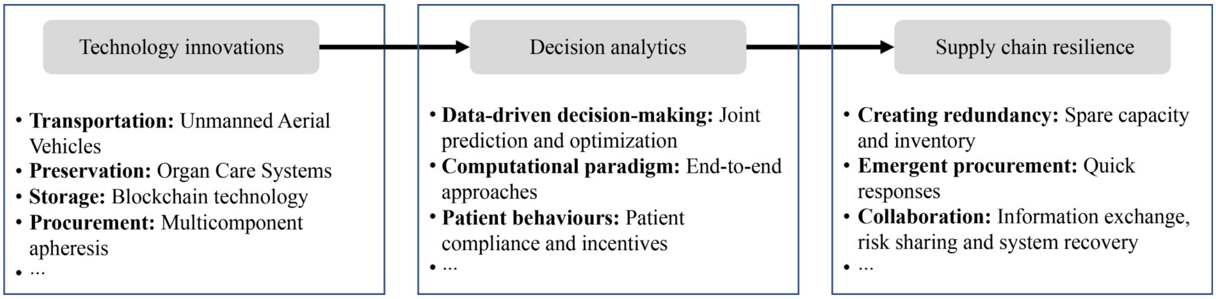


Fig. 3 Future research in perishable medical resource management.

maximizing the quality of organs and compatibility of blood types. Computational experiments validated the effectiveness of heuristic methods.

The design of service networks also entails shipping decisions, often involving the selection of transportation centers and modes, such as vehicles, trains, and airplanes. Caruso and Daniele (2018) presented a formulation in which different transportation services are represented by various links connecting transplant centers to donor hospitals, each incurring associated costs. Zahiri et al. (2014) proposed a multiperiod formulation that incorporates shipping agents to provide transportation services, aiming to minimize the total cost incurred by these agents. The case study included five transplant centers that performed heart and liver transplantation in Iran. Building on this application, Salimian and Mousavi (2022b) expanded the model to incorporate weather conditions as a factor in selecting transportation services. Hospitals opt for trains instead of airplanes to transport organs on rainy days to avoid potential delays. The numerical results demonstrated that considering weather conditions can lead to a 1.3% increase in the total cost of network design. In the context of transportation services with ground vehicles and airplanes, Rouhani and Amin (2022) further considered the assignment of hospitals to airports. Numerical experiments demonstrated that the resulting organ transplant network can significantly reduce transportation time, albeit requiring twice as many hospitals.

Deterministic supply is commonly assumed, with either estimated mean values based on data (Beliën et al., 2013; Rouhani and Amin, 2022) or predetermined values (Bruni et al., 2006; Zahiri et al., 2014; Salimian and Mousavi, 2022a). However, there are situations in which uncertain factors affecting supply require consideration. Blossey et al. (2022) investigated the uncertainty of the production approval time, referring to the duration of the approval process before pharmaceutical manufacturing. This uncertainty has implicit implications for decisions regarding outsourcing to contract manufacturing organizations. Heidari-Fathian and Pasandideh (2018) addressed the issue of uncertainty regarding donor groups during blood collection. The value of blood supply is uncertain but falls within a specific range. An uncertainty budget parameter is employed to adjust the level of protection against uncertainty.

System efficiency enhancement. Modifications to service networks are imperative to adapt to new changes and enhance operational efficiency. Academic literature provides illustrative examples of such modifications, particularly within the context of organ transplantation. These adaptations encompass reconfiguration of OPO regions, refinement of organ-matching protocols, and updates to organizational structures.

Kong et al. (2010) consolidated existing OPO regions into fewer and larger units to restructure the liver transplant network in the US. This restructuring endeavors to optimize regional benefits through viability-adjusted intraregional transplants. The authors measured the decay rate of donated livers by examining the percentage of primary nonfunctioning grafts. This decay rate is modeled either linearly or cubically in relation to organ transport distance. Demirci et al. (2012) extended this work by focusing on Pareto-efficient solutions that balance regional efficiency and equity in the US liver transplant network. Efficiency is evaluated through the expected viability-adjusted number of transplants, whereas equity is quantified by the aggregate rate of likelihood-adjusted intraregional transplants. Similarly, Gentry et al. (2015) undertook modifications in the US liver transplant network by consolidating 58 donor regions into fewer than 8 regions. The primary objective was to minimize disparities in the number of optimized donors versus actual donors across all regions. This study introduced a simulation framework to substantiate the substantial mitigation of regional disparities. Venugopal et al. (2013) delved into the hierarchical structure of organ matching, where donated organs are initially matched within a local region and then across larger regions. Their results underscore the geographic imbalance in the likelihood of successful matches across regions. Wang et al. (2022) conducted an empirical study to examine the positive impact of airline routes on kidney sharing. The findings revealed that the introduction of new airline routes can augment the average number of shared kidneys by 7.3%. Teng et al. (2014) embarked on the reconfiguration of organizational structures within regenerative medicine supply chains. The objective is to reduce treatment costs and enhance the success of live-cell therapies.

2.1 Problem features

To deepen our understanding of the strategic-level problems expounded in the aforementioned literature, we delve into distinct problem features pertaining to infrastructure specializations, transportation performance measurements, and the delicate equilibrium between fairness and efficiency.

Infrastructure specializations. The infrastructure within organ transplant networks comprises two primary components: OPOs and hospitals. OPOs are nonprofit entities tasked with coordinating and facilitating the organ donation and transplantation processes. This practice involves dividing geographical districts into multiple regions, with each region being serviced by a specific OPO. Hospitals, on the other hand, are categorized based on the services they offer, encompassing donor hospitals, transplant centers, and general hospitals. In most studies, donors and donor hospitals are not distinctly differentiated; instead, the focus is on the geographic locations of donor hospitals. For instance, Bruni et al. (2006), Kong et al. (2010), Demirci et al. (2012), and Caruso and

Daniele (2018) partitioned districts into OPOs to determine the optimal placement of donor hospitals. Only Rouhani and Amin (2022) explicitly assigned donors to donor hospitals and subsequently transported procured organs to transplant centers. Aside from donor hospitals, Salimian and Mousavi (2022a) exclusively identified suitable locations for hospitals capable of performing organ procurement surgeries.

Furthermore, the blood supply chain network has a structure analogous to that of an organ network. Collection units initially gather blood from donors and then transfer it to the blood centers for processing. Some collection centers maintain fixed locations, whereas others possess flexible locations during different periods. For instance, Heidari-Fathian and Pasandideh (2018) considered a time horizon of 250 periods to accommodate the variations in blood product demand and shelf life. It is noteworthy that, at the strategic level, there appears to be a gap in addressing the risk of network disruption, a facet underscored in the context of supply chain resilience.

Logistics challenges. Transportation time and distance play pivotal roles in service provision given the strict limitations on the preservation time of perishable medical resources. The objective functions and constraints in the service network design explicitly integrate transportation time and distance considerations. Bruni et al. (2006) formulated an optimization model to minimize the total terrestrial distance traveled by organs from donor hospitals to transplant centers. Heidari-Fathian and Pasandideh (2018) restricted the transplant-volume-weighted travel distance between blood facilities and donors within service coverage. Beliën et al. (2013) and Salimian and Mousavi (2022a) simultaneously factored the transportation time within the objective function and constraints. Salimian and Mousavi (2022b) specifically aimed to minimize aggregate time, including operation time in removal hospitals, travel time among facilities, and waiting time.

In contrast, transportation time and distance have been implicitly integrated into the parameters of the objective functions in other studies. Kong et al. (2010) and Demirci et al. (2012) adjusted the objective function by introducing a viability-adjustment multiplier that accounts for transportation distance, while Caruso and Daniele (2018) concentrated on minimizing the number of wasted organs that exceeded the cold ischemic time threshold. It is worth noting that the studies mentioned above predominantly consider deterministic delivery times, with Zahiri et al. (2014) exploring the potential influence of stochastic delivery times.

Fairness and efficiency. Service network design entails a delicate balance between fairness and efficiency, which is particularly important in the realm of organ transplantation. Currently, organ allocation systems prioritize hierarchical allocation based on regional demarcation. In nations such as the US and China, the emphasis lies on organ sharing within regions, prevailing over cross-regional sharing. Consequently, the primary focus is mitigating geographic disparities to achieve fairness. Demirci et al. (2012) concentrated on maximizing the minimum intraregional transplant rate among all OPOs, whereas Gentry et al. (2015) endeavored to minimize the disparity between optimized and actual donors across all regions. Rouhani and Amin (2022) quantified fairness in terms of travel distance and strived to minimize the maximum distance to transplant centers for each region. Patient equity has received attention from Bruni et al. (2006), who restricted the variance in the number of patients on waiting lists among subgroups of transplant candidates.

Efficiency, on the other hand, revolves around the minimization of total costs, encompassing nonmedical expenses such as transportation costs between facilities, facility construction costs, and penalties for unfulfilled requests. System efficiency is gauged through medical outcomes linked to transplant probability (Kong et al., 2010; Demirci et al., 2012).

2.2 Modeling methodologies

Various modeling methodologies have been harnessed to address strategic-level problems, including mathematical programming, discrete-event simulation, empirical regression, and geographical social network analysis. Mathematical programming formulations are prominent in more than half of the publications dedicated to creating service networks.

Mathematical programming techniques such as linear programming, integer programming (IP), and mixed integer programming (MIP) are employed to optimize facility locations and resource flows. For instance, MIP models with binary variables have been deployed to formulate shipping decisions (Caruso and Daniele, 2018; Rouhani and Amin, 2022). Exact-solution procedures are frequently employed to attain optimal solutions, particularly when dealing with relatively small-scale problems (Bruni et al., 2006; Beliën et al., 2013; Gentry et al., 2015). Heuristic methods were also employed to obtain feasible solutions within reasonable computation times. Kong et al. (2010) introduced a heuristic approach that employs local search operations to exchange OPOs between regions using branch-and-price procedures. Heidari-Fathian and Pasandideh (2018) utilized a Lagrangian relaxation approach with a subgradient method to update the Lagrangian coefficients. Numerical experiments illustrate that this method yields an averaged 1.38% gap in the objective values. Notably, our review identifies a dearth of exact-solution algorithms designed explicitly to solve large-scale problems.

A diverse array of optimization techniques is available for modeling strategic-level problems, including multi-objective optimization, chance-constrained optimization, and robust optimization. In the pursuit of efficiency and equity within the liver transplant system, Demirci et al. (2012) amalgamated these two objectives into a single objective using the widely employed weighted-sum approach. They proposed an MIP formulation that is amenable to general branch-and-price frameworks. Zahiri et al. (2014) formulated chance-constrained programs to ensure that delivery time constraints are met with a specified probability. They constructed fuzzy sets of uncertain parameters to facilitate tractable reformulations of MIPs. Rouhani and Amin (2022) harnessed robust multiobjective convex programs to ensure efficient transportation of donated organs to transplant centers. They assumed that demand and supply reside within a ball uncertainty set and employed the augmented constraint method to search for Pareto-efficient solutions. Alternative modeling approaches for uncertainty in robust optimization were applied in Salimian and Mousavi (2022a; 2022b)'s works. The majority of the surveyed papers establish tractable programs solvable by existing commercial solvers; otherwise, they provide approximation approaches. For example, Demirci et al. (2012) relaxed MIP into linear programming to obtain Pareto frontiers, and Salimian and Mousavi (2022a) employed metaheuristic algorithms to address nonlinear constraints.

Alternative modeling techniques, including network analysis, simulation modeling, and empirical studies, are employed to assess service networks and provide guidance for their enhancement. Venugopal et al. (2013) constructed a social network using organ transplantation data from the US to examine geographic disparities. Their analysis revealed that the current system tends to favor urban areas over rural ones. Subsequently, Gentry et al. (2015) utilized a discrete-event simulation tool to validate the designed liver allocation system. This tool assesses the disease progression of each patient on a waiting list using medical information obtained from patients with similar features. In terms of empirical studies, Wang et al. (2022) developed a difference-in-differences model that identifies a 7.3% increase in shared kidneys when direct flights are introduced. Robustness checks corroborate that direct flights exert a positive effect on the number of kidney transplants and negatively impact organ-discard rates.

3 Tactical-level problems

Tactical-level problems encompass challenges that manifest at a granular level and demand actionable strategies for daily operations. Within the sphere of perishable medical resource management, tactical-level predicaments typically center on the attainment of specific objectives and goals within an established service framework, unfolding over a medium- to short-term timeframe. In this comprehensive review, we scrutinized 49 papers addressing tactical-level conundrums. These quandaries pertain to the judicious deployment and orchestration of resources and services, mandating precise and efficient methodologies for executing targeted plans. Notably, one of the focal areas is inventory management, which explores optimal control policies for determining order quantities and inventory levels. Throughout the implementation of these plans, the behaviors of participants may diverge from socially desirable outcomes because of individual preferences or proprietary information. In response, mechanism design furnishes a spectrum of incentive mechanisms aimed at shaping participants' behaviors, thereby aligning them with socially optimal objectives and goals. Consequently, we categorized these studies into four distinct topics: Resource allocation, service scheduling, inventory management, and mechanism design.

Resource allocation. The distribution and allocation of medical resources are executed to fulfill specific objectives and cater to particular needs. Notably, in the realm of organ allocation, a prominent objective revolves around transplant rewards that reflect graft survival or quality-adjusted life expectancy. Su and Zenios (2005) proposed a kidney allocation policy that ensures that offers never decline under incentive compatibility, with their overarching objective being the maximization of total expected rewards. Zenios et al. (2000) introduced a dynamic index policy for kidney allocation, leveraging dynamic programming to augment quality-adjusted life expectancy while reducing mean waiting times. Bertsimas et al. (2013) fashioned a point system grounded in selected priority criteria with the aim of optimizing medical efficiency by approximating life-year gains from transplants. Sabouri et al. (2017) employed screening strategies to minimize the combined cost of anticipated screening expenses and penalty costs, effectively reducing the likelihood of ineligibility in matching kidneys. Perlman et al. (2018) devised an optimal dynamic allocation policy with state-dependent transition probabilities geared toward maximizing the expected transplant reward.

Additionally, fairness emerges as a pivotal consideration in organ allocation, where blood type incompatibility is a major source of inequality. van de Klundert et al. (2022) embarked on maximizing equity in waiting times and transplant probabilities, accounting for disproportionate arrival rates in subpopulations of different blood types. Furthermore, liver allocation policies have been explored by Thompson et al. (2004), Koyuncugil and Ozgulbas (2010), Akan et al. (2012), and Nemati et al. (2020).

Allocation of resources in screening tests for donated blood centers could mitigate transfusion-transmitted infectious (TTI) risk. Xie et al. (2012) developed mathematical models to minimize TTI risk while adhering to cost budgets and constraints related to blood waste. Their numerical experiments underscored that blood wastage can be averted when mitigating TTI risk, highlighting the significance of considering regional prevalence and coinfection rates. El-Amine et al. (2018) further contributed to this field by minimizing TTI risk using regret-based and expectation-based objectives. They established an uncertain set of prevalence rates to devise robust testing schemes.

A distinct line of research involves the evaluation of resource allocation performance, resulting in the development of novel indicators and measures. Koch (1996) introduced social worth criteria to assess the efficiency and fairness of organ transplantation. Devi et al. (2012) employed simulation models to estimate the average patient waiting time per year, whereas Bandi et al. (2019) proposed a novel method for estimating waiting times in multiclass queuing systems. Marinho and Araújo (2021) applied data envelopment analysis to evaluate the efficiency of organ transplants in Brazil, revealing the potential for a 45% increase in the utilization of organs without expanding the donor pool. Ouayogodé and Schnier (2021) delved into the effects of report card outcomes on patient selection through waiting-list registrations, highlighting the impact of information quality on patient registrations. Dhakate and Joshi (2020) and Delman et al. (2022) addressed issues related to the evaluation of organ allocation systems.

Service scheduling. The allocation of medical resources is a prelude to their organization and coordination, leading to the creation of schedules that delineate specific tasks, activities, and appointments for service provision. This facet primarily focuses on crafting regular schedules for blood collection by efficiently assigning staff and vehicles to collection sites during different periods.

Ayer et al. (2018) generated weekly schedules for collecting blood from multiple mobile sites, specifically for cryo production. To facilitate the transshipment of blood within 8 hours of collection, the collection window was divided into intervals. Moreover, research findings by Ayer et al. (2019) demonstrated a substantial reduction (approximately 40%) in per-unit collection costs when cryo and other blood products are concurrently produced. Özener et al. (2019) delved into the blood donation tailoring problem, seeking optimal collection schedules for donor pools. They embraced multicomponent apheresis, a novel collection technology that enables the collection of multiple blood components rather than whole blood. This innovative approach allows for tailored collection schedules to meet specific demands for blood products, potentially enhancing the efficient utilization of donor pools.

Collection scheduling has become an integrated endeavour when intertwined with appointment scheduling. Mobasher et al. (2015) merged blood collection and donation appointments into a unified model that harmonizes schedules at blood donation sites, ultimately maximizing platelet production. Furthermore, collection scheduling converges with inventory management to minimize the overall costs associated with blood collection, inventory holding, and disposal. Chen et al. (2019) embarked on making joint decisions concerning blood collection and platelet inventory control. Theoretical analysis revealed a substitution effect between blood collection and platelet production, indicating that increasing platelet inventory renders blood collection more attractive than platelet production.

The exploration of delivery routes has emerged as an additional dimension in the context of service schedules. Ghandforoush and Sen (2010) introduced a prototype decision-support system tailored to address the scheduling of shuttle services between collection sites and blood centers, primarily for platelet production. Optimization of delivery routes ensures that platelets are manufactured within a stringent six-hour window post-blood collection. Traditional vehicle routing problems featuring delivery time constraints have advanced for the transshipment of blood products. Pertinent references include Özener and Ekici (2018), Pirabán-Ramírez et al. (2022), and Xu and Szmerekovsky (2023).

Inventory management. Effective inventory management is of paramount importance when dealing with perishable healthcare products, primarily because of their limited shelf life. The shortened lifespan of these products increases the risk of waste and shortages, thereby adding to the intricacy of inventory management. A prevalent approach in this domain is the periodic review strategy, which involves reviewing the inventory level at fixed time intervals. Zhou et al. (2011) analyzed a periodic review inventory system tailored to fixed-lifetime items. Notably, this inventory system incorporates dual sourcing for regular and expedited replenishment. Duan and Liao (2013) contributed to the field by developing a periodic review inventory system designed to handle perishable items with varying lifetimes. The objective of this system is to minimize the expected wastage rate due to expiration while adhering to a predetermined level of unsatisfied demand. Additionally, the substitution of products with different lifetimes was explored by Civelek et al. (2015) and Noble et al. (2022). In their respective studies, products with longer lifetimes could fulfill the demand for products with shorter lifetimes, albeit with associated penalties.

A variety of methodologies are at the disposal of researchers to analyze inventory systems in this context. Bar-Lev et al. (2017) derived the fluid and diffusion limits of the blood inventory process by considering Poisson supply and demand. Ultimately, the diffusion limit process follows the Ornstein–Uhlenbeck process. Lowalekar and Ravi (2017) applied the theory of constraints to discern the causes of blood shortages and wastage. Their simulation-based approach demonstrated the potential of the proposed theory of constraint solution in reducing annual platelet shortages and wastage by 82% and 98%, respectively. Bhandawat et al. (2022) explored the role of blockchain-based contracts in facilitating collaborative decision making within blood inventory systems.

An order-up-to policy is a common practice in replenishment. Under this policy, the order quantity is determined based on a selected base stock level, which is contingent on the total on-hand inventory at the commencement of each period. Duan and Liao (2013) explored a modified order-up-to policy that integrates partial information on stock-age distribution. In the context of perishable platelets differentiated by various lifetimes, Noble et al. (2022) concluded that the order-up-to policy surpasses the fixed-order quantity policy. Abouee-Mehrizi et al. (2022) introduced a feature-driven approach to ascertain the base stock level for each period. In their study, the base stock level hinges on a linear decision rule, constituting a linear combination of demand features. Further applications of order-up-to policies have been explored by Zhou et al. (2011) and Chen et al. (2019). Civelek et al. (2015) employed a fixed-order quantity policy, where the order quantity remains constant across all periods.

Mechanism design. Mechanism design is the focal point in designing rules or mechanisms to attain desired outcomes when individuals possess varying preferences or private information. The objective is to motivate individuals to act in ways that lead to socially desirable outcomes. In our review, the majority of studies concentrate on developing incentive tools aimed at influencing the behavior of resource consumers. Su and Zenios (2006) offered incentives to transplant candidates, encouraging them to provide accurate information about their types, thereby enabling them to join appropriate transplant queues. Ata et al. (2017) induced transplant candidates to self-select multiple register regions, thereby enhancing geographical equity in waiting times. Su and Zenios (2004) demonstrated that a first-come-first-served approach can result in excessive organ waste, whereas a last-come-first-served approach can optimize organ utilization. Ata et al. (2021) affirmed that ranking patients based on kidney quality can substantially reduce survival mismatches and kidney waste. The behaviors of transplant candidates in mechanism design problems were further explored in the works of Mendonça et al. (2020), Nageswaran and Scheller-Wolf (2022), and Tunç et al. (2022). Zhang et al. (2020) devised a rationing game to recover surplus medical products and meet the demands of underserved healthcare facilities in developing nations.

The development of incentive mechanisms to influence resource suppliers' behavior has also garnered attention. We note that the literature has paid limited attention to exploring donor behavior. Dai et al. (2020) presented a framework to analyze the impact of donor-priority rules on social welfare. These proposed donor priority rules incentivize organ supply by prioritizing registered organ donors for future organ transplantation. Misra et al. (2022) considered coordinating organizations, such as the government, to balance social welfare and economic costs. They suggested determining an optimal reimbursement fee to incentivize hospitals' efforts in organ retrieval. Nagurney and Dutta (2019) developed a game-theoretic model for blood donation organizations. The model examines the competitive mechanism between organizations, as they compete to attract blood donors by offering high-quality services in different regions, with the Nash equilibrium existing at the level of service quality. Regarding drugs, Lan et al. (2022) proposed a Stackelberg game between a pharmaceutical manufacturer and a retailer. The manufacturer employs an encroachment mechanism that threatens to introduce a direct sales channel for drugs. Under certain conditions, this manufacturer encroachment leads to a win–win outcome when the perceived drug quality and the out-of-pocket percentage of the offline drug's price are at moderate levels.

3.1 Problem features

To gain a deeper understanding of the tactical-level problems elucidated in the literature mentioned above, we delve into aspects concerning optimization objectives, uncertainty identification, and incentive instruments.

Optimization objectives. The optimization objectives in organ transplantation prioritize nonfinancial goals, with a primary focus on social welfare. The queue discipline is an effective tool for influencing social welfare. As validated by Su and Zenios (2004), a first-come-first-serve approach amplifies patients' inclination to decline offers of marginal quality, whereas a last-come-first-serve strategy can achieve better organ utilization. Tunç et al. (2022) prioritized candidates returning to the waitlist for retransplants who accepted a predefined set of organs in exchange for their position on the waitlist. This priority queue simultaneously enhances organ utilization and social welfare.

Information sharing is another effective means of improving social welfare. Su and Zenios (2006) found that truthful reporting of patient types benefits both high- and low-risk candidates in terms of social welfare. However, maximizing social welfare does not always require the provision of complete information. According to Nemati et al. (2020), patients have the option of reducing the frequency of information updates to avoid additional updating costs. Furthermore, many studies have employed multicriteria objective functions. For instance, Akan et al. (2012) aimed to minimize the number of patients who passed away while maximizing the total quality-adjusted life years. Su and Zenios (2006) proposed two distinct social welfare functions: One that considers aggregate utility to represent efficiency and another that considers the minimum utility to represent equality. Nemati et al. (2020) developed a model to determine health reporting requirements that simultaneously minimize two conflicting criteria: Inequity due to information asymmetry and the burden of updates.

In contrast, optimization objectives related to healthcare products tend to emphasize financial goals over nonfinancial ones. Inventory problems often involve multiple criteria, such as holding and shortage costs (Lowalekar and Ravi, 2017; Bhandawat et al., 2022). A specialized financial objective related to perishable items is the minimization of expiration costs owing to limited preservation time, as observed by Zhou et al. (2011) and Noble et al. (2022). In resource-scheduling problems, multicriteria objectives encompass collection and transportation costs (Ayer et al., 2019; Chen et al., 2019). Additionally, nonfinancial objectives related to healthcare products vary based on the research question. Sabouri et al. (2017) aimed to minimize the likelihood of organs being assigned to ineligible patients who develop severe conditions, such as cardiovascular disease. El-Amine et al. (2018) developed a robust blood-screening scheme that minimizes the risk of infectious blood donations by considering budget constraints at blood centers.

Uncertainty identifications. The demand for perishable medical resources is a significant source of uncertainty. In the literature, several studies have treated demand as a deterministic parameter. For instance, Özener et al. (2019) and Noble et al. (2022) modeled blood product demand deterministically. However, given the unpredictable and variable nature of healthcare demand, deterministic assumptions regarding demand patterns may not always hold true. Stochastic demand is more commonly adopted in the literature. For instance, in more than half of the mechanism design problems employing queuing models, Poisson demand rates are assumed (Nageswaran and Scheller-Wolf, 2022; Tunç et al., 2022). It is worth noting that the existing literature still lacks a systematic exploration of realistic demand patterns, with the exception of Chen et al. (2019), who adopted a data-driven approach without relying on specific distribution assumptions.

Furthermore, existing literature also investigates ways to mitigate demand uncertainty through demand prediction. Twumasi and Twumasi (2022) compared various machine-learning algorithms for forecasting blood demand in a hospital in Ghana. The forecasting error ranged from 12.55% to 19.36%, depending on the applied machine learning algorithm. The uncertainty can also be attributed to other factors. In the formulation by Perlman et al. (2018), donated kidneys arrive stochastically in the system over time. Regarding the received organ, Zenios et al. (2000) assumed that the organ may fail, whereas Su and Zenios (2005) considered organ type as a stochastic variable. Sabouri et al. (2017) incorporated three stochastic variables related to disease development, transplantation, and mortality.

Incentive instruments. Incentive instruments serve as valuable tools for shaping patient behavior and promoting socially desirable outcomes. Mechanism design problems in the literature employ various incentive instruments with a specific emphasis on queuing disciplines. Dai et al. (2020) and Nageswaran and Scheller-Wolf (2022) permitted multiple queues, representing waiting lists on which transplant candidates can register. This approach is considered equitable for all candidates when their arrival rate, restricted to a single waiting list, follows a consistent distribution (Dai et al., 2020). To effectively implement this approach, Nageswaran and Scheller-Wolf (2022) proposed offering affordable jet services to remote areas. Su and Zenios (2004) and Dai et al. (2020) demonstrated the use of priority as an incentive instrument. Su and Zenios (2004) illustrated that a last-come-first-serve approach can optimize organ utilization, while Dai et al. (2020) revealed that implementing the donor-priority rule can enhance overall social welfare.

In addition to priority, information sharing plays a crucial role in the application of incentive instruments (Su and Zenios, 2006; Nemati et al., 2020; Zhang et al., 2020). In Su and Zenios (2006), candidates strategically provide their types to join the queue, whereas in Nemati et al. (2020), candidates regularly report updates on their health conditions. Zhang et al. (2020) confirmed that randomly sharing inventory information, based on self-reported preferences for healthcare products, constitutes an optimal policy for allocating medical surplus products.

3.2 Modeling methodologies

In this subsection, we discuss the different modeling methodologies employed to address tactical-level problems in the reviewed literature. These methodologies include queuing and game theory, optimization techniques, and evaluation approaches.

Queuing theory and game theory are prominent features in tactical-level publications, especially when tackling resource allocation and mechanism design problems. Queueing theory finds frequent applications in calculating the waiting times of transplant candidates, classified into distinct types based on their medical scores. Multiclass queuing models have been developed, both without priority (Su and Zenios, 2006; Nageswaran and Scheller-Wolf, 2022) and with priority (Dai et al., 2020; Tunç et al., 2022) considerations. Patients may exit the queueing system prematurely, for instance, owing to unfortunate circumstances such as passing away while waiting. Approaches employing fluid approximations were applied by Akan et al. (2012), Ata et al. (2017), and Dai et al. (2020) to analyze queuing systems involving reneging in organ transplants. Nagurney and Dutta (2019) and Lan et al. (2022) employed game theory but did not integrate queues into their models. Nagurney and Dutta (2019) developed a game-theoretic model for blood donation organizations competing based on service quality, whereas Lan et al. (2022) proposed a Stackelberg game between a pharmaceutical manufacturer and a retailer, considering the manufacturer's potential encroachment on selling channels.

Optimization techniques are the cornerstone of most studies on tactical-level problems. Deterministic optimization models are more commonly employed in resource scheduling problems (Ayer et al., 2018; Özener and Ekici, 2018; Özener et al., 2019; Pirabán-Ramírez et al., 2022) than in inventory management issues (Noble et al., 2022). MIP was formulated to ensure optimal schedules for blood collection (Mobasher et al., 2015). Stochastic optimization is employed to address demand uncertainty, which captures dynamic demand in multiple stages (Xu and Szmerekovsky, 2023). Dynamic programming was applied by Ayer et al. (2018; 2019) to solve multistage stochastic optimization models. Some publications, such as Duan and Liao (2013) and Lowalekar and Ravi (2017), combined simulation and optimization to minimize inventory costs using metaheuristic methods. However, data-driven and robust optimization approaches remain relatively underrepresented, with the exception of El-Amine et al. (2018) and Chen et al. (2019).

Evaluating the performance of organ allocation systems is approached diversely depending on the specific evaluation measures developed. Under the assumption of multiclass queuing systems, Bandi et al. (2019) provided a robust estimation approach to determine the waiting times of transplant candidates. Devi et al. (2012) relied on simulation models to estimate the same parameter. Marinho and Araújo (2021) assessed the efficiency of decision-making in organ transplants using data envelopment analysis, while Dhakate and Joshi (2020) evaluated the efficiency of organ donation through a newly proposed inquiry model. Delman et al. (2022) employed straightforward statistical analysis, leveraging historical data to estimate the utilization rate of the kidneys.

4 Operational-level problems

Operational-level problems persist at the lower echelons, necessitating individual and real-time responses to dynamic decision environments. In the realm of perishable medical resource management, these operational-level challenges revolve around individual-level real-time decision-making. Notably, these challenges pertain to the intricate domain of organ matching between donors and recipients, a facet that has hitherto not garnered explicit attention at strategic and tactical levels. The operational-level literature encompasses 29 papers that have been categorized into three overarching themes: Service mechanisms, service innovations, and service evaluations. Service mechanisms delve into a patient's dynamic decisions regarding the optimal timing for matching. Service innovations explore scenarios in which pairs of donors and recipients engage in organ swaps while considering the associated risk of matching failure. Finally, service evaluations scrutinize the outcomes stemming from organ matching.

Service mechanisms. Patients are confronted with a pivotal decision when considering whether to accept organ offers promptly or await future potential offers. The timing of acceptance assumes paramount significance, as it hinges on dynamic factors encompassing the patient's health status and the quality of available organs, both of which are subject to change over time. Alagoz et al. (2004) discerned the sufficient conditions underpinning the control-limit policy, an approach that maximizes quality-adjusted life expectancy concerning living-donor livers. This foundational work was further elaborated by Alagoz et al. (2007a), who incorporated the option of cadaveric livers, culminating in the identification of an at-most-three-region policy. Subsequently, Alagoz et al. (2007b) shifted the paradigm by considering organ arrival probability as a function contingent on the patient's state, eschewing the assumption of a constant parameter. Boloori et al. (2020) undertook the intricate task of striking a balance between mitigating organ rejection and curbing the development of diabetes attributable to immunosuppressive drugs. Their case studies revealed that judicious decisions pertaining to medication timing and dosage can enhance patient life expectancy by up to 4.58% while simultaneously reducing medical expenditures by up to 11.57%.

Efforts to enhance acceptance decisions are also made by leveraging patients' private information. One avenue entails information sharing, as elucidated by Sandıkçı et al. (2008), who introduced the concept of a patient's "price of privacy". This metric gauges the value of having access to comprehensive waiting list information. The provision of such information empowers patients to make acceptance decisions that translate into a 5% boost in life expectancy compared to navigating the decision-making process devoid of informative cues. Building upon this, Sandıkçı et al. (2013) revealed that even divulging partial information holds the potential to nullify a patient's "price of privacy". Furthermore, they concluded that the price of privacy, as it stands in current US United Network for Organ Sharing (UNOS) practice, is negligible.

An alternative avenue involves information inference, as exemplified by Zhang (2010), who deployed a dynamic choice model that enables patients to infer organ quantity by observing the selections made by fellow patients. This approach maximizes the anticipated present discounted value. Complementing this, Erkin et al. (2010) presented an inverse approach that aids in inferring patient preferences under diverse health states. This inference is facilitated by monitoring the sequence of patients' acceptance decisions.

Service innovations. Organ exchange programs represent a recent and innovative initiative that facilitates organ exchange between donor and recipient pairs. In certain instances, two pairs may exhibit incompatibility with each other, but essential compatibility may exist between the first donor and the second patient, and vice versa. In such scenarios, potential arises for a life-saving match to be realized. While most research on organ exchange programs predominantly focuses on short matching cycles and chains, an exception emerges in the work of Glorie et al. (2014), who delved into cycles and chains with lengths exceeding 4 and 6, respectively.

The foremost challenge encountered in organ exchange programs is achieving compatibility between donors and patients, as mismatches frequently arise. One approach to address this challenge involves assigning compatibility probabilities to each edge within an organ exchange graph. Anderson et al. (2017), Ding et al. (2018), Ashlagi et al. (2019), and Blum et al. (2020) explicitly factored in compatibility probabilities prior to conducting crossmatch tests. In this context, Anderson et al. (2017) assumed that the compatibility probability remains independent of pool size. Ding et al. (2018) proposed a two-phase random walk procedure aimed at establishing independent transplant chains and cycles. The utility of a cycle is gauged by the product of the cumulative weights of its constituents and their compatibility probabilities. Ashlagi et al. (2019) introduced the consideration of heterogeneous compatibility probabilities among patient types with the overarching objective of establishing stringent bounds for patients' waiting time limits. Finally, Blum et al. (2020) pivoted their attention to the selection of subsets of edges with the aim of maximizing the overall compatibility probability within the organ exchange graph.

An alternative approach to address this challenge involves constructing an uncertainty set of compatibility to mitigate the likelihood of matching failures (Carvalho et al., 2021; Smeulders et al., 2022). Carvalho et al. (2021) presented a robust model that adapted matching procedures before detecting incompatibilities through precise crossmatch tests. Smeulders et al. (2022) also explored a similar uncertainty set and attempted to select a subset of donor-patient pairs within transplant chains for subsequent crossmatch testing. For a more comprehensive understanding of organ exchange programs and their practical applications, one can delve into the studies of Zenios (2002), Dickerson et al. (2019), Klimentova et al. (2023), and Carvalho and Lodi (2023). Additional insights into real-world applications of organ exchange programs can be obtained from the comprehensive examination conducted by Anderson et al. (2015).

Service evaluations. Evaluating transplant performance both predictively and prescriptively offers invaluable insights into the practical application of decision-making tools. Predictive analysis empowers health care professionals to anticipate the likelihood of transplant success or failure. This often involves leveraging individual-level data, including the comprehensive profiles of both donors and recipients. For instance, Oztekin et al. (2011) forecasted the graft lifespan and functional status of lung transplants using 25 explanatory features. Similarly, Al-Ebbini et al. (2016) predicted the same indicators with a more compact set of eight explanatory features by employing fuzzy rules. Their experiments demonstrated that the constructed fuzzy-rule-based system achieved a prediction accuracy of approximately 80%. Misiunas et al. (2016) used artificial neural networks to predict the functional status of recipients across 12 levels. To enhance the reliability of their predictions, they incorporated data envelopment analysis during the preprocessing phase to identify and eliminate outliers. Topuz et al. (2018) predicted graft survival for kidney transplants using a Bayesian belief network by employing features preselected using machine learning techniques. Notably, the health status of recipients emerged as a significant factor in predicting survival times.

On the other hand, prescriptive analysis equips healthcare professionals with the means to assess pivotal influencing factors within a transplant system. Cook et al. (1990) applied the analytic hierarchy process to rank candidates on a waiting list, evaluating them based on five key indicators: Logistics, compatibility, waiting time, financial considerations, and medical status. Yuan et al. (2002) prioritized recipients using fuzzy rules and considered eight features to evaluate transplant performance. Levy (2005) analytically derived the minimum probability of transplant success, considering the conditions of both donors and recipients. Consequently, transplant surgeries were not recommended when the calculated minimum probabilities of transplant success were deemed to be too low. Anand et al. (2021) empirically validated the benefits of postsurgical care education, revealing its positive impact on 30-day readmission rates and patient satisfaction through difference-in-difference estimations.

4.1 Problem features

The objective of this section is to offer further insights into operational-level concerns found in the relevant literature. In the following paragraphs, we discuss the modeling characteristics related to patient stratification, risk-averse attitudes, and uncertainty identification.

Patient stratifications. Patients are stratified into several groups based on relevant factors such as health status and immune sensitivity. This approach enables healthcare providers to personalize care plans, resulting in improved health outcomes and more efficient utilization of healthcare resources. In the context of organ acceptance mechanisms, patients are stratified based on their time-dependent health status (Alagoz et al., 2004; Erkin et al., 2010; Zhang, 2010; Boloori et al., 2020). Health state is a comprehensive indicator of laboratory values and waiting-time measurements. The Markovian transition between health states is commonly considered when patients undergo dynamic changes in their health over time. The likelihood of patients receiving an organ of a specific quality level may vary depending on their health status (Alagoz et al., 2007a; 2007b; Batun et al., 2018).

Furthermore, in the context of innovations in organ exchange services, patients are stratified based on their immune sensitivity. Specifically, patients are categorized into either highly sensitized or nonhighly sensitized groups (Ding et al., 2018; Ashlagi et al., 2019; Dickerson et al., 2019; Carvalho et al., 2021; Smeulders et al., 2022). Highly sensitized patients were confined to a very small percentage of potential donors. Consequently, there is a relatively high probability of transplant failure.

Risk-averse attitudes. Most publications assume that patients are risk neutral concerning the transplant reward. However, this assumption may not hold true, as individuals display varying degrees of risk aversion or risk acceptance. Several studies have examined the influence of risk-averse attitudes on organ acceptance decisions. Zhang (2010) employed a quadratic utility function in which a patient's utility for accepting a kidney offer increases with the kidney's quality, resulting in a concave curve. Consequently, the utility derived from the mean value of kidney quality surpasses the average utility derived from all possible kidney quality values. Batun et al. (2018) considered the exponential utility function, which exhibits both increasing and concave characteristics regarding the duration of survival after accepting or rejecting a kidney. As patients become more risk averse, the optimal course of action for sicker patients is to accept higher quality livers. In this review, topics that discuss the risk attitudes of patients undergoing organ transplantation remain unexplored.

Uncertainty identifications. Compatibility between donors and recipients remains the primary source of uncertainty in organ matching. To address this uncertainty, matching failures are considered. Dickerson et al. (2019) modified the expected utility of organ matching by incorporating failure probabilities. In this context, the utilization of failure-aware kidney exchanges can substantially enhance the anticipated number of lives saved, as substantiated by theoretical analysis and numerical experiments. Similarly, Smeulders et al. (2022) adjusted the utility function of organ matching by employing a sample average approximation, primarily to alleviate the computational burden within their two-stage stochastic program. Carvalho et al. (2021) explored a more robust formulation of organ matching, aiming to maximize the utility of organ matching under worst-case scenarios. Consequently, highly sensitized patients are better protected against matching failures.

Another source of uncertainty arises from the health status of patients. To address this uncertainty, transition probabilities between health states were utilized. Whereas most studies assume deterministic transition probabilities between patient states in the service mechanisms of organ acceptance, Boloori et al. (2020) deviated by permitting variations within an uncertainty set.

4.2 Modeling methodologies

This subsection examines various modeling methodologies employed for each reviewed problem at the operational level, encompassing the Markov decision process (MDP), optimization techniques, and evaluation approaches. Specifically, we explored diverse approaches to address the inherent issue of computational feasibility in optimization models.

MDPs find widespread application in organ acceptance decisions, enabling patients to make informed choices regarding organ offers. A typical MDP model for organ transplantation comprises states, actions, and rewards. Beyond patient health states, several publications have also considered the quality of the offered organs (Alagoz et al., 2007a; 2007b; Batun et al., 2018). The actions of organ recipients primarily involve accepting or rejecting organ offers, and the rewards assigned to them typically reflect the benefits and risks associated with these states and actions. The theoretical analysis involves the introduction of specific assumptions about reward functions. For example, Alagoz et al. (2007a; 2007b) assumed a monotonically nonincreasing reward function based on the quality level of offered livers, while Zhang (2010) and Batun et al. (2018) proposed reward functions with quadratic and exponential forms, respectively. The state transition is formulated using the transition probabilities. As mentioned earlier, deterministic transition probabilities are commonly estimated from data, with the exception of Boloori et al. (2020), who constructed an uncertainty set of transition probabilities.

Various optimization techniques have been applied to model organ exchange programs, depending on the uncertainties inherent in organ transplant procedures. Deterministic IP is a foundational approach for formulating the assignment of cycles and chains (Glorie et al., 2014; Ding et al., 2018; Klimentova et al., 2023). However, other studies have focused on capturing stochasticity and uncertainty (Dickerson et al., 2019; Carvalho et al., 2021; Smeulders et al., 2022). Dickerson et al. (2019) proposed a stochastic optimization framework that can accommodate matching failures with stochastic failure rates. They presented an IP formulation of the optimization model with the constraint of maximum cycle length. Smeulders et al. (2022) developed a two-stage stochastic optimization approach that considers the uncertainty in the results of cross-match tests before the selection of patient-donor pairs. Carvalho et al. (2021) provided a robust optimization method by generating an uncertainty set encompassing all possible transplant scenarios.

Furthermore, the issue of computational tractability is critical in organ exchange programs. As the size of the exchange graphs increases, the number of chains increases exponentially, rendering the problem intractable for standard solvers. In such cases, the common approaches involve heuristic algorithms or approximation methods. Glorie et al. (2014) proposed a generic iterative branch-and-price algorithm that exhibits polynomial-time solvability for the pricing problem. Ding et al. (2018) presented a hybrid algorithm that combined random sampling and column generation techniques to approximate the optimal solution. Dickerson et al. (2019) demonstrated that the proposed failure-aware clearing problem can be solved in polynomial time if the cycle length is less than two; otherwise, a branch-and-price-based optimal clearing algorithm is proposed. Smeulders et al. (2022) leveraged existing algorithmic approaches, such as branch-and-cut and Benders decomposition, to solve the IP relaxation of proposed problems. In addition to mathematical programming techniques, Carvalho and Lodi (2023) formulated an organ exchange program as a decentralized and noncooperative game, obtaining computational Nash equilibrium instances generated from real data.

Machine learning and decision-making tools appear to be attractive tools for transplant performance evaluation. Machine-learning models have been widely adopted in predictive analyses. Oztekin et al. (2011) focused on forecasting graft lifespan and functional status for lung transplants using decision trees, whereas Topuz et al. (2018) predicted graft survival for kidney transplants using Bayesian belief networks. Conversely, decision-making tools are prevalent in prescriptive analysis. A typical tool is a fuzzy decision system that evaluates potential organ allocation outcomes. Yuan et al. (2002) assessed the likelihood of a successful kidney transplant using a fuzzy logic system, while Al-Ebbini et al. (2016) estimated the transplant survival time and functional status for lung transplants using a fuzzy allocation system. More straightforward rules for organ allocation are recommended by Cook et al. (1990), Levy (2005), and Anand et al. (2021), who addressed difference-in-difference estimation to evaluate post-surgical education.

5 Summary and future research

The COVID-19 pandemic has garnered significant attention in the management of perishable medical resources. Severe scarcity and extreme perishability represent two significant challenges in the handling of these resources. The review encompasses 93 publications spanning 1990 to 2022, revealing an increase in annual publications from one paper in 1990 to 18 papers in 2022. All the reviewed publications have been categorized into three groups: Strategic, tactical, and operational level problems. Several promising avenues for future research have emerged, summarized as follows.

Research on service innovations. Several innovative technologies have been introduced to enhance the system efficiency. UAVs have emerged as transportation innovations, with one notable application being the delivery of automated external defibrillators (Chan et al., 2018). However, the operationalization of large-scale UAV networks presents challenges for providing real-time services. Boutilier and Chan (2022) developed an integrated location-queuing model that incorporated quick response times. This model can also integrate donor management policies, which has not been fully explored in the literature.

Another noteworthy preservation innovation is the Organ Care System (OCS), a commercially available device that significantly extends the preservation time for donated organs. Equipping hospitals with OCSs faces constraints related to budget limitations at donor hospitals and potentially introduces regional disparities by affecting matching probabilities and organ supply. Kong et al. (2010) proposed a set covering model that addresses the design of service regions, providing a foundation for investigating the impact of OCSs on efficiency and equity.

Blockchain represents a storage innovation that can ensure the privacy and security of health data. Gong and Zhao (2020) introduced the concept of a health data bank through a blockchain. However, applications of blockchain technology in this context are relatively scarce. In conclusion, service innovations hold promising prospects for future research.

Research on decision analytics. Decision analytics in healthcare research presents numerous valuable opportunities. In the current era of big data, studies are increasingly demanding data-driven decision-making. The prevalent approach in the literature involves separate prediction and optimization formulations, underlining the need for joint prediction and optimization frameworks, as exemplified by the framework developed by Zhu et al. (2022).

Linear prediction models, such as the linear decision rule, are widely utilized, posing challenges when extended to nonlinear models. A promising and practical framework is the end-to-end computational paradigm (Qi et al., 2023). In this paradigm, deep learning is employed to fit prediction models and enhance prediction accuracy, whereas optimal decisions are approximated using historical data and observed features. Consequently, this high-performance computational paradigm has the potential to offer real-time solutions that satisfy the swift response requirements essential for managing perishable medical resources.

In the realm of medical resource coordination, studies also require decision analytics concerning patient behavior. Patient compliance poses a significant challenge, as patient behavior often deviates from medical recommendations. Intervention tools, such as incentive payments, prove effective in mitigating these deviations (Suen et al., 2022). Thus, a supply-responsive demand-intervention perspective deserves consideration.

Research on supply chain resilience. Supply chain resilience embodies the adaptive capacity to respond to disruptions and effectuate a timely and efficient recovery (Tukamuhabwa et al., 2015). The perishable nature of medical resources presents unique challenges in developing adaptive capabilities.

Creating redundancy, such as spare capacity and inventory, represents a straightforward approach. However, this strategy can be costly, especially when dealing with medical resources that have a limited lifespan. Conversely, emergent procurement offers a more economical alternative but may fall short in delivering swift responses (He et al., 2016). Therefore, a mixed-strategy approach may be more effective in cultivating resilience.

Furthermore, collaboration is a prominent approach that involves cooperative efforts in information exchange, risk sharing, and system recovery (Liu et al., 2023). For instance, dialysis centers collaborated in treatments during the COVID-19 pandemic. Urgent demands necessitate prompt attention and underscore the need for proactive collaboration. In the literature, collaborative games serve as valuable tools for constructing medical alliances by aligning the interests of the participants.

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