A Multicriteria Decision-Making Perspective on Healthcare Operations, Logistics and IT Interoperability

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Abstract. This position paper explores healthcare operations and logistics from a multicriteria decision-making (MCDM) perspective, emphasizing the integration of operations research (OR) models with healthcare information technology (HIT). It reviews key OR problem classes, including timetabling, facility location, resource allocation, inventory management, supply chains, and routing, and synthesizes the performance criteria and trade-offs among efficiency, cost, patient outcomes, equity, resilience, and sustainability. We argue that classical and modern MCDM techniques are shown to reveal and balance these trade-offs, guiding model formulation and governance in complex healthcare systems. Beyond methodological aspects, we call for two complementary integrations. The first is horizontal integration: interoperability-by-design across peer healthcare IT and logistics platforms (e.g., EHRs, laboratory and imaging systems, asset and inventory management, and supplier interfaces) so that OR models can reliably read and write executable data and actions. The second is vertical integration: alignment of decisions, uncertainty treatments, and information hand-offs across planning horizons, operationalized through a four-level hierarchy of real-time (H1), operational (H2), tactical (H3), and strategic (H4). This hierarchy aligns problems, decision methods, and information hand-offs across horizons, linking rapid response and scheduling at lower levels with long-term capacity planning and governance at higher levels. The paper concludes with a research agenda focused on (i) multiobjective modeling that elevates equity and sustainability as primary design goals, (ii) interoperability-by-design frameworks connecting OR tools with healthcare IT infrastructures, and (iii) time-scale-aware optimization combining robust, stochastic, and learning-augmented methods to achieve adaptive, reliable, and data-driven healthcare logistics.

Keywords: Healthcare logistics, Multicriteria decision-making, Operations research, Interoperability, Time-scale-aware optimization, Equity, Sustainability

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1 Introduction

Healthcare logistics shapes access, outcomes, and the efficient use of scarce resources [8]. Demands for better care and cost control require decision processes that can weigh several goals at once. Multicriteria decision-making (MCDM) provides such a basis by making trade-offs explicit and comparable [49, 71, 94, 120]. In this paper, we take a position that healthcare operations should be planned and controlled with a *multiobjective and multidisciplinary* lens, where equity and sustainability stand alongside cost, service, and clinical outcomes as first-class criteria [59, 61, 90, 259, 274, 280].

We ground this view in key OR problem classes that recur across health systems: timetabling of appointments, staff, and equipment [22, 69, 100, 138, 199, 235]; facility location and coverage [7, 13, 95, 107, 108]; resource allocation of personnel, budgets, and devices [186]; inventory and supply chains [54, 56, 207, 246, 288]; and routing for emergency response and distribution [266]. Across these topics, MCDM allows quantitative and qualitative criteria to be combined and discussed with stakeholders in a transparent way.

Two forms of integration are needed for these models to matter in practice. We use the terms *horizontal* and *vertical* integration in a complementary, axis-based sense. *Horizontal integration* concerns interoperability and coordination *across* peer systems, departments, and organizations operating at comparable decision levels—for instance, linking EHR data streams with inventory, laboratory, imaging, and supplier platforms to enable end-to-end logistical visibility and model-driven execution [62, 115]. *Vertical integration* concerns coherence *across time scales*, ensuring that real-time control, operational scheduling, tactical policy setting, and strategic design exchange machine-readable targets, constraints, and feedback signals [6, 98, 126, 189, 212, 277].

The second is *vertical* integration across planning horizons and uncertainty profiles. We adopt the healthcare planning hierarchy and make the real-time layer explicit: strategic, tactical, operational, and real-time control (H4–H1) [148]. This ordering assigns the right problems and methods to the right time scale and clarifies hand-offs. Strategic and tactical levels set networks, capacities, contracts, buffers, and targets; operational planning produces feasible rosters and appointment books; real-time control adjusts to arrivals, no-shows, traffic, and device failures within minutes and hours. Uncertainty also changes by horizon: deep uncertainty and stress testing at H4, non-stationary demand and lead times at H3, scenario or chance constraints at H2, and rolling-horizon repairs with short-term forecasts at H1. In Section 5, Table 1 summarizes this H1–H4 scheme and the associated methods and data flows, which we view as the backbone for closed-loop, evidence-based operations.

Our contribution is to articulate this combined agenda. We argue for multiobjective models that treat equity and sustainability as core goals, for interoperability-by-design that links OR with healthcare IT, and for time-scale-aware optimization that matches methods to horizon and uncertainty. The remainder of the paper reviews the main OR problem classes in healthcare, discusses MCDM and performance criteria, develops the case for IT integration and interoperability, and then presents the H1–H4 framework for vertical alignment before outlining conclusions and future directions. See Fig. 1 for a two-dimensional integration map illustrating horizontal interoperability across peer systems and vertical alignment across the time scales H1–H4.

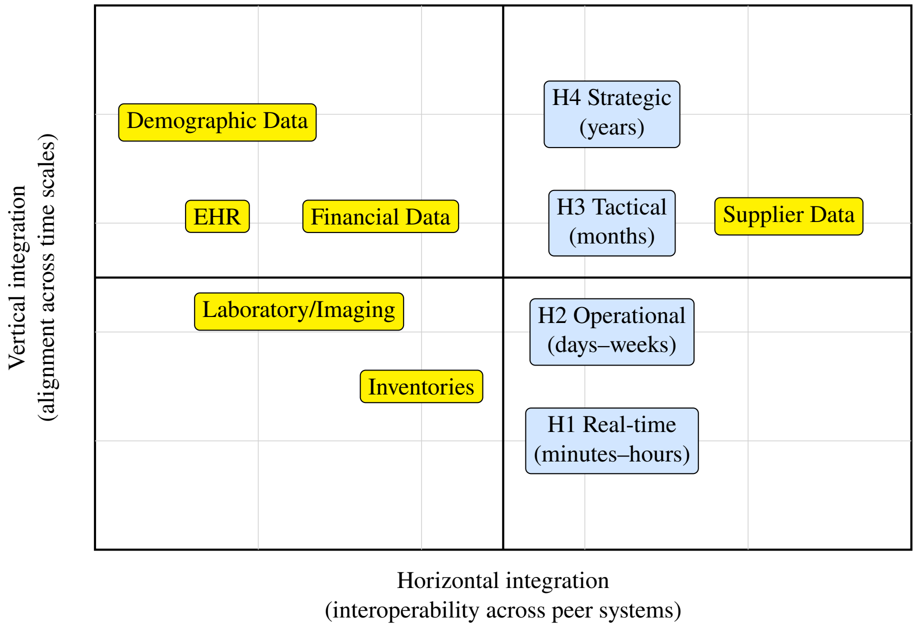

Fig. 1. A 2D integration map highlighting horizontal interoperability across peer systems (marked in yellow) and vertical alignment across time scales H1–H4 (marked in blue).

The remainder of the paper is structured as follows. Section 2 maps the main OR problem classes in healthcare, including timetabling, facility location, resource allocation, inventory, supply chains, and routing. Section 3 defines the performance criteria, key trade-offs, and the MCDM toolbox used to balance them. In Section 4, the focus is on *horizontal integration* through healthcare IT interoperability, showing how OR tools connect to *peer* digital systems (EHRs, asset and inventory platforms, laboratory and imaging systems, and supplier interfaces) to support data quality, AI/IoT enrichment, and executable decision support. Section 5 develops the concept of *vertical integration* across time scales (H1–H4) and uncertainty profiles, aligning short-term operations with long-term strategic planning. Section 6 closes with conclusions and a research agenda on multiobjective modeling, interoperability-by-design, and time-scale-aware optimization.

2 Different Types of Operations Research Problems in Healthcare

This section addresses *horizontal integration* through Healthcare Information Technology (HIT). Here, horizontal integration denotes interoperability and coordination across *peer* digital platforms that support clinical and logistical workflows, enabling OR models to be embedded as decision services that consume standardized data and produce executable outputs.

2.1 Timetabling

In this section, we discuss the challenges of scheduling within healthcare systems, including patient appointment scheduling [138, 199], staff rostering [55, 100], and resource utilization [69, 235]. We also describe multicriteria approaches to balancing efficiency, patient satisfaction, and operational costs. Scheduling within healthcare systems presents significant challenges due to the need to balance competing priorities. Patient appointment scheduling must account for individual needs, specialist availability, and case urgency while minimizing patient wait times and ensuring equitable access to care [132]. Staff rostering involves optimizing shift patterns to meet patient demand while adhering to legal and contractual obligations, maintaining staff satisfaction, and preventing burnout [99]. Resource utilization, including operating rooms, medical equipment, and diagnostic facilities, requires careful synchronization to maximize capacity and minimize downtime or bottlenecks [69].

Multicriteria decision-making approaches are increasingly used to address these challenges by integrating efficiency, patient satisfaction, and operational cost considerations [223]. For instance, hybrid optimization techniques, combining linear programming, heuristic algorithms, simulation models, and the use of artificial intelligence (AI) and machine learning (ML) models, have shown promise in creating schedules that achieve a balance between conflicting objectives [19, 178]. Patient satisfaction is often enhanced by reducing waiting times and ensuring timely access to specialists, while operational costs are managed through efficient resource allocation and the minimization of overtime expenses [3]. These methods often incorporate stochastic models to account for the inherent variability in healthcare demand and resource availability. Additionally, advances in AI and ML provide dynamic, real-time scheduling adjustments to respond to unforeseen disruptions, such as staff absences or emergency cases, further enhancing system resilience [17, 178]. By integrating patient-centric metrics with operational efficiency goals, these multicriteria approaches ensure a holistic and adaptive solution to the timetabling complexities inherent in healthcare systems.

The scheduling of patient appointments is particularly challenging in outpatient clinics, where fluctuating patient arrival rates and no-show rates can significantly disrupt planned schedules [12, 86]. Predictive analytics, using historical data and machine learning, can forecast patient behavior, allowing clinics to strategically overbook or adjust schedules dynamically. This approach not only optimizes resource utilization but also mitigates patient dissatisfaction caused by long wait times [220]. In surgical scheduling, another area of critical importance, block scheduling methods, and constraint programming are frequently used to efficiently allocate operating rooms. These methods reduce surgery delays and ensure that high-priority cases are accommodated while maintaining balance with elective procedures [281]. Furthermore, the introduction of priority-driven frameworks ensures equitable care delivery while adhering to operational constraints.

Staff rostering presents its own set of challenges, particularly in settings with 24/7 operational requirements, such as emergency departments and intensive care units [216]. Ensuring compliance with labor regulations, equitable shift distribution, and minimizing overwork are critical concerns. Agent-based simulation models, combined with evolutionary algorithms, have been used to design robust rostering solutions that account for both the personal preferences of healthcare workers and the institutional requirements of hospitals [66]. Moreover, integrating workforce availability with real-time demand forecasts enables adaptive rostering, where schedules are dynamically updated to address unexpected staff shortages or surges in patient admissions. Such adaptive systems contribute to reducing burnout and improving overall job satisfaction among healthcare workers.

Resource utilization, particularly for high-demand facilities such as diagnostic imaging centers and intensive care units, requires a delicate balance between operational efficiency and patient-centered care. Capacity planning models that incorporate simulation-based optimization enable healthcare providers to forecast demand, allocate resources effectively, and minimize delays in service delivery. For instance, the queueing theory has been widely applied to model patient flow and identify bottlenecks, allowing administrators to make evidence-based decisions regarding resource allocation [129]. The advent of digital twins (i.e., virtual replicas of healthcare systems) provides an innovative tool for testing scheduling scenarios and optimizing resource usage in a risk-free environment [20].

Despite these advancements, many challenges persist. Healthcare systems often encounter resistance to change, particularly when adopting new scheduling technologies or methodologies. Moreover, the fragmented nature of healthcare delivery systems can create silos, hindering the seamless integration of timetabling solutions across departments. Addressing these issues requires a multidisciplinary approach that engages stakeholders at all levels, including administrators, clinicians, and patients. Policies that promote collaboration, data sharing, and the adoption of interoperable technologies are crucial for overcoming these barriers and ensuring the successful implementation of advanced timetabling solutions.

In conclusion, timetabling in healthcare systems is a complex and multifaceted challenge that requires innovative, data-driven approaches to ensure efficiency, patient satisfaction, and cost-effectiveness. Advances in optimization techniques, artificial intelligence, and predictive analytics offer valuable tools to address these challenges, but their successful implementation relies on overcoming organizational, technological, and cultural barriers. Future research should prioritize the development of more adaptive, patient-centered, and resilient scheduling systems to meet the evolving demands of healthcare delivery.

2.2 Facility Location

This section explains the importance of facility location in healthcare logistics, addressing criteria such as accessibility, demand satisfaction, and cost minimization. At the end, we introduce relevant multicriteria models for optimizing facility location. The location of the facility plays an essential role in healthcare logistics, serving as a fundamental determinant of the efficiency, accessibility, and overall quality of healthcare services [13]. The strategic positioning of healthcare facilities significantly influences the ability to address patient demand, reduce costs, and ensure equitable access to medical resources [13]. Accessibility is a paramount criterion, as facilities must be located within a reasonable distance (known as service distance [33, 36]) from the populations they are intended to serve. This is particularly crucial in rural or underserved regions, where transportation barriers can exacerbate health disparities [80]. Ensuring proximity to densely populated or high-demand areas is essential for timely care delivery, especially for emergency services, where every minute can mean the difference between life and death [292].

Demand satisfaction is another critical factor in facility location. Facilities must be located where patient needs are highest, which requires robust demand forecasting methods to identify current and future healthcare needs. For example, demographic and epidemiological analyses can guide the placement of specialized centers, such as oncology or dialysis clinics, in areas with a higher incidence of relevant conditions [273]. Incorporating demand variability into location models enables planners to design resilient systems that can adapt to evolving healthcare needs without compromising service quality.

Cost minimization, while vital for sustainability, must be balanced with accessibility and quality. The costs related to land acquisition, construction, personnel, and operational logistics must be optimized to ensure long-term viability. Location-allocation models, which integrate spatial and financial data, are widely used to minimize these costs while maintaining acceptable service levels [142]. These models often utilize optimization techniques such as integer programming or heuristic/metaheuristic methods to identify the most cost-effective configurations.

Multicriteria decision-making models are used to optimize facility location in healthcare logistics [73, 91]. These models integrate various criteria, such as accessibility, cost, demand, and equity, into a unified framework. For instance, the p-median model focuses on minimizing the distance between demand points and facilities, thereby enhancing accessibility [87]. In contrast, the maximal covering location problem (MCLP) seeks to maximize the population covered within a predefined service radius, ensuring broader reach [33, 36]. Hybrid models, which combine the characteristics of the p median model and MCLP, have been developed to address complex challenges in the real world, such as balancing the healthcare needs of urban and rural populations [85]. To optimize facility location in healthcare logistics, multicriteria decision-making models (MCDM) are frequently employed. These models help to evaluate multiple criteria simultaneously, ensuring that the chosen location meets various essential requirements [35, 37]. MCDM models are essential tools in optimizing facility location in healthcare logistics. They provide a structured approach to evaluate multiple criteria, incorporate stakeholder preferences, and ensure that the chosen location meets various essential requirements. By using methods such as FITradeoff [92], ELECTRE I [9], Data Envelopment Analysis (DEA) [105], Geographic Information System (GIS) [47], and Analytic Hierarchy Process (AHP) [147], decision-makers can make informed and balanced decisions that enhance the efficiency and effectiveness of healthcare logistics.

Advanced approaches, such as those incorporating GIS, provide visual and analytical tools for facility location optimization. GIS-based models enable spatial analysis of demographic data, transportation networks, and service coverage, allowing planners to make data-driven decisions [64, 79, 236]. Additionally, the integration of stochastic models addresses uncertainties in demand, travel times, and resource availability, making them particularly valuable in dynamic healthcare environments [28, 97].

Equity is increasingly recognized as a critical criterion in facility location planning [265]. Ensuring that underserved populations have equitable access to healthcare services requires models that prioritize fairness alongside efficiency. For instance, incorporating equity constraints into location models helps ensure that vulnerable groups, such as low-income populations or those in remote areas, are not disproportionately disadvantaged [198].

Despite these advancements, several challenges persist in optimizing facility locations [7]. Data limitations, such as inaccurate demand forecasts or incomplete demographic information, can undermine the effectiveness of location models. Moreover, political and economic constraints often influence decision-making, sometimes resulting in suboptimal placements. Addressing these barriers requires collaboration among stakeholders, robust data collection efforts, and the adoption of flexible, adaptive models capable of accommodating changing conditions.

In conclusion, facility location is a fundamental aspect of healthcare logistics, directly impacting the accessibility, efficiency, and equity of healthcare delivery [13]. Multicriteria models and advanced analytical tools offer valuable frameworks for optimizing facility placement, but their success hinges on addressing data limitations, fostering stakeholder collaboration, and integrating equity considerations. As healthcare demands continue to evolve, future research should prioritize the development of more dynamic, inclusive, and data-driven approaches to facility location planning.

2.3 Resource Allocation

In this section, we present the complexities of resource allocation in healthcare, such as staffing, equipment, and budget distribution. We discuss multicriteria strategies for optimizing resource use under constraints like budget and patient care quality. The allocation of resources in healthcare is an inherently complex and multifaceted process that involves the distribution of limited resources such as staffing, medical equipment, and budgetary funds to meet the ever-growing demands for healthcare services [43, 46]. The challenge lies in balancing operational efficiency, equitable access, and high-quality patient care. Staffing allocation, for example, requires aligning workforce availability with patient demand while also considering factors such as skill mix, employee satisfaction, and compliance with labor regulations [99]. Inefficient staffing can result in overburdened healthcare workers, higher burnout rates, and compromised patient outcomes, emphasizing the need for robust and adaptive scheduling systems.

Equipment allocation is another critical component, particularly for high-demand and expensive technologies such as diagnostic imaging machines, ventilators, and surgical instruments. The uneven geographic distribution of these resources can create disparities in healthcare access, especially in underserved or rural areas [128]. Allocation strategies often incorporate predictive models to anticipate demand patterns and ensure optimal utilization of equipment. For instance, queueing theory and simulation models have been applied to reduce waiting times and improve throughput in radiology departments [144].

Budget distribution represents a third pillar of resource allocation, requiring decision-makers to prioritize competing needs within financial constraints. Investments must be directed toward infrastructure, personnel, and technology in ways that maximize return on investment and align with broader health policy objectives [217]. Budgetary decisions are further complicated by uncertainties in healthcare demand, inflation, and changes in policy or reimbursement structures. Multicriteria decision-making models have proven instrumental in navigating these complexities, allowing administrators to evaluate trade-offs between cost efficiency, patient satisfaction, and clinical outcomes [29, 134, 187, 249].

Multicriteria optimization approaches are widely applied to address resource allocation challenges in healthcare [71]. Linear programming, for instance, has been utilized to allocate operating room time across different surgical specialties, maximizing utilization while minimizing delays [68]. Heuristic algorithms and artificial intelligence are increasingly employed to solve more complex, non-linear allocation problems, enabling real-time adjustments to resource plans to accommodate sudden changes, such as staff absences or surges in patient volume. Additionally, game theory models have been explored to resolve conflicts in resource allocation, such as disputes over limited funding among departments, by promoting cooperative and equitable solutions [196]. Multicriteria optimization approaches are extensively applied to address resource allocation challenges in healthcare due to their ability to consider multiple objectives and constraints simultaneously. In the personnel allocation problem, multicriteria optimization models, such as those using mixed integer programming and weighted-sum approaches, have been applied to allocate personnel in healthcare services. These models help in balancing different objectives, such as cost, efficiency, and service quality, by adjusting problem parameters and using tools like AMPL and CPLEX [254, 255]. In hospital settings, dynamic resource allocation is crucial due to the stochastic nature of patient arrivals and treatment processes. Multiobjective Evolutionary Data Analysis (EDA) has been used to optimize strategies for resource allocation, making the solutions understandable and applicable in real-world scenarios [151]. Utility functions (UF) have been employed in hospital case-mix planning to distribute resources among different operating units. This approach helps in evaluating trade-offs between different stakeholders' objectives and provides a better capacity allocation [65]. Multiobjective simulation optimization models, integrating techniques like non-dominated sorting particle swarm optimization (NSPSO) and multicriteria computing budget allocation (MOCBA), have been developed to optimize resource allocation in emergency departments. These models aim to minimize patient length of stay and resource wastage [74]. Multicriteria decision analysis (MCDA) is used to prioritize healthcare interventions by considering various criteria such as health outcomes, cost-effectiveness, and equity. This approach helps in making transparent and rational decisions for resource allocation [44, 134]. A framework based on MCDA has been developed to improve reimbursement prioritization for rare diseases. This framework considers multiple criteria, including effectiveness, disease severity, and economic considerations, to ensure equitable and transparent decision-making [2]. Multiobjective planning methods have been used to construct patient allocation models during major epidemics. These models consider factors like illness severity, hospital level, and resource fairness to generate balanced and effective allocation schemes [293]. These multicriteria optimization approaches provide robust frameworks for addressing the complex and dynamic nature of resource allocation in healthcare, ensuring that multiple objectives and constraints are effectively balanced.

One of the most significant challenges in resource allocation is ensuring equity. Resource distribution must account for not only efficiency but also fairness, ensuring that vulnerable populations, such as those in low-income or remote communities, have equitable access to healthcare services. Equity-focused models, including those that incorporate social determinants of health, have been developed to prioritize resource allocation for underserved groups while maintaining overall system performance [63, 134, 186, 193].

Technological advancements, particularly in data analytics and artificial intelligence, are revolutionizing resource allocation practices. Predictive analytics utilizes historical and real-time data to forecast future resource needs, while AI-driven decision support systems optimize resource allocation under complex and dynamic conditions [168]. Digital twins, i.e., virtual replicas of healthcare systems, provide a novel platform for simulating different allocation scenarios, enabling administrators to test strategies and evaluate their impact before implementation [1, 114, 283].

Despite these innovations, barriers such as data silos, organizational resistance, and ethical considerations often impede effective resource allocation. Overcoming these challenges requires collaboration among stakeholders, the establishment of robust data governance frameworks, and the development of policies that align resource allocation with ethical principles and public health goals.

In conclusion, resource allocation in healthcare requires navigating complex trade-offs between efficiency, equity, and quality, all within the constraints of budgets and fluctuating demand. Multicriteria strategies, supported by advanced technologies, provide powerful tools for optimizing resource use. However, their success depends on addressing systemic barriers and ensuring that ethical and equity considerations remain central to the decision-making process.

2.4 Inventory Management

In this section, we detail the logistics of managing medical inventories, including pharmaceuticals, medical supplies, and personal protective equipment (PPE). We analyze multicriteria decision-making approaches to minimize stockouts while controlling costs. Effective inventory management in healthcare is essential to ensuring the continuous availability of critical items, such as pharmaceuticals, medical supplies, and PPE. Proper logistics for managing these inventories directly influence patient care quality, operational efficiency, and cost control. The inherent complexity lies in balancing competing objectives, such as minimizing stockouts, controlling costs, and maintaining an adequate supply of critical resources amid fluctuating demand.

Pharmaceutical inventory management, in particular, requires precision, as shortages can have severe consequences for patient outcomes [10, 233]. Inventory policies for pharmaceuticals often utilize forecasting models to predict demand based on historical consumption patterns, seasonality, and emerging health trends [145]. Techniques such as just-in-time (JIT) inventory are widely applied to reduce holding costs while ensuring timely availability [185]. However, this approach necessitates robust supply chain coordination and contingency planning to mitigate potential disruptions [72, 125].

Medical supplies, including consumables such as syringes, gloves, and bandages, require efficient tracking and replenishment systems to prevent waste due to expiration or obsolescence. Automated inventory systems, integrated with hospital information systems, enable real-time tracking of stock levels and usage rates, providing actionable insights for procurement decisions [182]. Additionally, the integration of barcode or RFID

(Radio Frequency Identification) technology further improves accuracy and efficiency in inventory management processes.

PPE inventory management has gained significant attention, particularly during global health crises like the COVID-19 pandemic [141]. Ensuring an adequate supply of masks, gowns, and gloves while managing sudden surges in demand requires agile and scalable inventory strategies. Multicriteria decision-making models, such as the Analytical Hierarchy Process (AHP) and fuzzy logic, have been employed to prioritize procurement and distribution based on factors like demand urgency, supplier reliability, and cost [78].

Minimizing stockouts while controlling costs is a primary objective in healthcare inventory management [251]. Stockouts not only disrupt operations but also compromise patient safety. Techniques such as Economic Order Quantity (EOQ) and ABC analysis are used to categorize inventory items based on their criticality and consumption value, allowing personalized management strategies [137]. For example, high-value and high-priority items are closely monitored and ordered in smaller, more frequent batches to ensure availability, whereas low-priority items are managed with less frequent restocking.

The use of multicriteria decision-making approaches has proven effective in optimizing inventory management. Linear programming models, for example, enable healthcare facilities to allocate budgetary resources efficiently across diverse inventory categories, ensuring a balance between cost and availability [217]. Stochastic models address uncertainties in demand and supply, allowing for dynamic adjustments to inventory policies as conditions evolve [155]. Furthermore, machine learning algorithms are increasingly employed to predict demand patterns and optimize inventory levels in real time, significantly enhancing decision-making capabilities [10, 205]. Multicriteria decision-making (MCDM) approaches have proven effective in optimizing inventory management by addressing the complexity and conflicting criteria inherent in inventory control. Inventory management involves various conflicting objectives, such as minimizing costs while maximizing service levels. MCDM approaches help in balancing these objectives by considering multiple criteria simultaneously [118, 171, 256]. Traditional inventory management methods often focus on a single criterion like cost or demand, which do not fully capture the complexity of modern supply chains. MCDM methods, on the other hand, incorporate multiple criteria, making them more robust and comprehensive [225, 240]. Combining MCDM with machine learning techniques can significantly improve inventory management decisions. For instance, a hybrid framework using fuzzy logic, AHP, and VIKOR for SKU ranking, followed by ML models for demand forecasting, has shown improved accuracy and decision-making agility [222]. The integration of MCDM with optimization algorithms, such as the MOPSO algorithm combined with TOPSIS, helps generate diverse and superior solutions for inventory control problems, catering to various decision-maker preferences [118]. In the pharmaceutical sector, a three-phase hybrid approach using MCDM techniques and data analytics has been proposed to optimize inventory management. This approach includes process characterization, multicriteria ABC classification, and the application of forecasting models to establish reorder points [164]. A study on multi-echelon inventory systems in the public sector demonstrated the effectiveness of MCDM methods in selecting the best inventory policies, taking into account the costs and responsiveness of the supply chain [257].

Effective inventory management requires collaboration among various stakeholders. MCDM approaches facilitate better communication and decision-making by involving different areas of the company and considering their inputs [225]. A distributed inventory control approach using MCDM techniques can improve the performance of logistics processes by ensuring that decisions are well-communicated and agreed upon by all stakeholders involved [225]. In the health sector, MCDM methods have been used to classify and manage inventory more effectively, ensuring the availability of critical supplies while optimizing costs [32]. MCDM approaches are essential for optimizing inventory management in today's complex and dynamic business environments. By considering multiple criteria and integrating advanced techniques, these methods enhance decision-making, improve accuracy, and ensure better alignment with organizational goals and stakeholder needs. The practical applications and case studies highlight the versatility and effectiveness of MCDM in various industries, making it a valuable tool for inventory optimization.

Despite advancements, inventory management in healthcare continues to face several challenges. Supply chain disruptions, inaccurate demand forecasts, and a lack of interoperability between inventory and procurement systems often result in inefficiencies. Overcoming these issues requires investment in advanced technologies, such as blockchain for traceability and AI-driven analytics for demand forecasting [93, 158, 241]. Additionally, collaborative partnerships between healthcare providers, suppliers, and policymakers are essential for building resilient supply chains capable of withstanding disruptions.

In conclusion, effective inventory management is a cornerstone of healthcare logistics, ensuring the timely availability of essential resources while maintaining cost control. Multicriteria decision-making models, supported by advanced technologies, provide robust solutions to address the complexities of managing medical inventories. However, the success of these strategies relies on continuous innovation, stakeholder collaboration, and a commitment to developing adaptive and resilient inventory systems.

2.5 Supply Chain Management

In this section, we examine the healthcare supply chain, including procurement, transportation, and distribution. We also focus on multicriteria optimization to balance efficiency, responsiveness, and cost-effectiveness. Supply chain management in healthcare is a critical function that ensures the availability and timely delivery of essential medical resources, such as pharmaceuticals, medical equipment, and consumables [117]. It involves several interrelated activities, such as procurement, transportation, and distribution, all of which must be meticulously coordinated to achieve efficiency, responsiveness, and cost-effectiveness. The unique characteristics of healthcare, including unpredictable demand patterns, stringent regulatory requirements, and the critical nature of resources, make supply chain management both complex and indispensable to patient care.

Procurement in healthcare supply chains involves the strategic sourcing of materials and services to meet the operational requirements of healthcare providers. Supplier selection is a critical aspect of procurement, where multicriteria decision-making approaches are often employed to evaluate factors such as cost, quality, reliability, and delivery lead times. For instance, the Analytical Hierarchy Process (AHP) has been widely used to prioritize suppliers based on their ability to meet these criteria [52]. Moreover, fostering long-term partnerships with suppliers, supported by contracts that ensure accountability and compliance, is essential for maintaining a resilient supply chain [183].

Transportation is another essential component of healthcare supply chains. The timely and secure delivery of medical supplies, particularly temperature-sensitive items like vaccines and biologics, requires specialized logistics solutions. Cold chain logistics, which utilize temperature-controlled transportation and storage systems, are crucial for maintaining the efficacy of sensitive pharmaceuticals [103]. Multimodal transportation strategies, combining road, air, and rail, are frequently employed to enhance reach and responsiveness while optimizing costs. Additionally, advanced tracking systems utilizing IoT and GPS technologies have significantly improved the transparency and efficiency of transportation processes [262].

Distribution, the final link in the healthcare supply chain, focuses on delivering resources to end-users, such as hospitals, clinics, and pharmacies. Efficient inventory management systems, including automated replenishment and real-time stock tracking, are essential for ensuring resource availability while minimizing overstock and waste. Distribution networks are increasingly adopting hub-and-spoke models to optimize storage and delivery routes, particularly in regions with dispersed populations [125]. During emergencies, agile distribution strategies are crucial for swiftly reallocating resources and ensuring continuity of care.

Multicriteria optimization plays a crucial role in balancing efficiency, responsiveness, and cost-effectiveness across the supply chain. Optimization models often incorporate techniques such as linear programming, heuristic algorithms, and simulation to address complex trade-offs. For example, minimizing transportation costs must be balanced with the need for rapid response times, particularly during emergencies or pandemics. Furthermore, stochastic models account for uncertainties in demand and supply, enabling supply chain planners to develop robust and adaptive solutions [155]. Multicriteria optimization is essential in balancing efficiency, responsiveness, and cost-effectiveness in the healthcare supply chain. This approach involves considering multiple conflicting objectives to enhance overall supply chain performance. Techniques like the Multiobjective Gray Wolf Optimizer (MOGWO), Non-Dominated Sorting Genetic Algorithm II (NSGA-II), and Multiobjective Differential Evolution Algorithm (MODEA) are employed to generate high-quality Pareto solutions [18, 162]. The epsilon constraint method helps in understanding trade-offs between different objectives, such as cost and environmental impact [42]. Optimization models have been applied to pharmaceutical supply chains to demonstrate their efficacy in real-life contexts, balancing cost, environmental impact, and service levels [18, 42, 162]. Models have been developed to optimize drug purchasing and distribution in hospitals, integrating financial and logistical decisions to maximize performance [173]. A generalized network optimization model has been developed for the blood supply chain, addressing critical issues like optimal allocations and supply-side risks [209]. Multicriteria optimization in healthcare supply chains involves balancing various objectives to achieve efficiency, responsiveness, and cost-effectiveness. By employing advanced optimization techniques and integrating modern technologies, healthcare organizations can enhance their supply chain performance, ultimately improving patient care and operational efficiency.

Technological advancements are revolutionizing healthcare supply chain management. Blockchain technology is increasingly being adopted to enhance transparency, traceability, and security in procurement and transportation processes [275]. Artificial intelligence and machine learning enable predictive analytics to forecast demand patterns, optimize inventory levels, and improve decision-making. Additionally, digital twins (virtual simulations of supply chains) provide a powerful tool for testing and refining strategies before their real-world implementation [114]. The integration of technologies such as IoT, AI, and blockchain can enhance supply chain performance by improving data accuracy, reducing errors, and optimizing resource distribution [219, 253].

Despite these advancements, challenges persist in optimizing healthcare supply chains. Fragmentation among supply chain actors, a lack of standardization, and limited data sharing often hinder coordination and efficiency. Regulatory compliance, particularly in cross-border transportation of medical goods, adds another layer of complexity. Overcoming these challenges requires collaborative efforts among stakeholders, investments in advanced technologies, and the establishment of governance frameworks that promote interoperability and transparency.

In conclusion, effective supply chain management in healthcare is crucial for ensuring timely access to critical resources, optimizing operational costs, and improving patient outcomes. By using multicriteria optimization and advanced technologies, healthcare supply chains can become more resilient, responsive, and efficient. Future research should prioritize integrating innovative solutions, such as AI and blockchain, with traditional supply chain practices to address emerging challenges and support sustainable healthcare delivery.

2.6 Routing

In this section, we analyze the challenges in healthcare-related routing problems, such as emergency vehicle routing [82] and medical supply delivery [272]. We also discuss how multicriteria decision-making can enhance routing efficiency and responsiveness. Routing in healthcare logistics is a critical operational area that significantly affects patient outcomes and service delivery efficiency [282]. Challenges in healthcare-related routing span various aspects, including emergency vehicle routing and medical supply delivery [149, 177]. These problems are often complicated by factors such as time constraints, geographic barriers, traffic conditions, and unpredictable demand patterns [34, 194, 266]. Tackling these challenges requires innovative strategies and robust decision-making frameworks that optimize both efficiency and responsiveness.

Emergency vehicle routing presents a unique set of challenges due to the urgent nature of the services provided. Ambulances and other emergency vehicles must navigate urban traffic congestion, respond to unpredictable demand spikes, and optimize routes to minimize response and transport times. Geographic Information Systems (GIS) and real-time traffic data have become indispensable tools for improving routing efficiency in emergency services [57]. Dynamic routing models that incorporate real-time updates on traffic conditions and road closures can significantly reduce response times and improve patient survival rates [139, 176]. Additionally, these systems must address equity in service delivery, ensuring that underserved areas are not disproportionately impacted by routing decisions [238].

Medical supply delivery routing presents unique challenges, particularly when handling temperature-sensitive items like vaccines and biologics. Maintaining the cold chain during transport requires carefully planned routes that minimize travel time and avoid disruptions. In rural or remote areas, poor infrastructure further complicates delivery logistics, necessitating innovative solutions such as drone-based deliveries, which have shown great promise in overcoming accessibility barriers [243]. Furthermore, fluctuating demand during pandemics or natural disasters can place significant strain on existing delivery networks, highlighting the need for scalable and flexible routing systems to ensure uninterrupted supply.

Multicriteria decision-making (MCDM) approaches play a crucial role in improving routing efficiency and responsiveness. These methods integrate multiple objectives, such as minimizing travel time, reducing fuel costs, ensuring equitable service distribution, and adhering to regulatory constraints. For instance, the Analytical Hierarchy Process (AHP) and Multiobjective Optimization (MOO) are widely used to evaluate and prioritize competing routing objectives, allowing decision-makers to select optimal solutions that balance efficiency and equity [294]. Additionally, stochastic models enhance these approaches by accounting for uncertainties in demand and environmental conditions, making them particularly effective in dynamic and unpredictable scenarios [139].

Advanced technologies, such as artificial intelligence (AI) and machine learning (ML), are revolutionizing healthcare routing by enabling predictive and adaptive systems. AI-driven algorithms can analyze historical data and real-time inputs to predict demand hotspots, optimize route planning, and dynamically adjust schedules. For example, reinforcement learning has been employed to develop self-optimizing routing systems that continuously improve through feedback [276]. Furthermore, the integration of Internet of Things (IoT) devices facilitates real-time monitoring of vehicle performance and environmental conditions, ensuring that routing decisions remain adaptive and data-driven [11, 53, 230].

Despite these advancements, several challenges persist in optimizing healthcare routing. Data fragmentation, limited interoperability among systems, and the high costs associated with implementing advanced technologies remain significant barriers. Additionally, ethical considerations, such as ensuring equitable access to emergency services and minimizing the environmental impact of routing decisions, require careful attention. Overcoming these challenges demands collaborative efforts among healthcare providers, policymakers, and technology developers to create integrated, scalable, and sustainable routing solutions.

In conclusion, routing in healthcare logistics is a complex yet critical domain that demands a balance between efficiency, responsiveness, and equity. Multicriteria decision-making frameworks and advanced technologies provide powerful tools to tackle the inherent challenges of healthcare-related routing problems. Future research should prioritize integrating emerging technologies, such as AI and IoT, with traditional MCDM approaches to develop adaptive and resilient routing systems capable of addressing evolving healthcare needs.

3 Multicriteria Decision-Making in Healthcare Logistics

Healthcare logistics involves the intricate management of resources, processes, and operations to deliver high-quality care to patients efficiently and sustainably. Multicriteria decision-making (MCDM) has emerged as a critical approach for addressing the multifaceted challenges inherent in healthcare logistics, where diverse and often conflicting objectives must be balanced. Unlike traditional decision-making methods that typically focus on a single criterion, such as cost or efficiency, MCDM integrates multiple performance criteria, including patient satisfaction, cost-effectiveness, operational efficiency, and equity in resource allocation. Given the dynamic nature of the healthcare sector and its critical importance to human well-being, decision-making frameworks must comprehensively address these interdependencies [23, 45, 102].

In healthcare logistics, MCDM is particularly valuable for optimizing systems such as supply chain management, resource allocation, facility location, inventory management, and routing. Each of these domains requires balancing trade-offs between key performance indicators, such as minimizing costs while maximizing service levels or ensuring accessibility while maintaining operational feasibility [125]. Additionally, the integration of advanced computational models and artificial intelligence has significantly enhanced the applicability of MCDM by enabling decision-makers to analyze large datasets, model complex systems, and generate actionable insights. By incorporating diverse perspectives from stakeholders, including patients, healthcare providers, and policymakers, MCDM frameworks provide a holistic approach to addressing the multifaceted challenges of healthcare logistics.

The following subsections explore specific aspects of MCDM in healthcare logistics. Section 3.1 discusses the key metrics used to evaluate healthcare operations. Section 3.2 examines the relationships and trade-offs between these metrics. Finally, Section 3.3 explores how advanced models and methodologies are applied to achieve optimal outcomes. Together, these discussions underscore the critical role of MCDM in advancing healthcare logistics and ensuring the sustainability of healthcare systems.

3.1 Performance Criteria of Operational Healthcare

The operational performance of healthcare systems is evaluated using a range of criteria that measure efficiency, quality, accessibility, and sustainability. These criteria serve as essential benchmarks to ensure that healthcare logistics meet the dual objectives of patient satisfaction and cost-effectiveness while addressing broader societal and organizational goals. Multicriteria decision-making (MCDM) methodologies utilize these performance metrics to guide optimization processes and support evidence-based decision-making. The primary performance criteria for operational healthcare can be broadly categorized into efficiency metrics, patient-centric measures, financial performance, and equity considerations.

Efficiency in healthcare operations typically emphasizes resource utilization, throughput, and timeliness. Key metrics include bed occupancy rates, the average length of stay (ALOS), patient flow in emergency departments (EDs), and operating room efficiency [130]. High efficiency ensures optimal utilization of resources such as staff, facilities, and equipment, minimizing bottlenecks and waste. For example, reducing patient wait times in EDs directly impacts both resource efficiency and patient satisfaction [14, 250]. Similarly, metrics such as operating room turnover rates [188] and the scheduling efficiency of diagnostic equipment [161, 210] are critical for measuring operational productivity.

Healthcare operations are inherently patient-focused, with criteria such as patient satisfaction, clinical outcomes, and continuity of care serving as critical indicators of success. Surveys measuring patient satisfaction often assess experiences related to wait times, communication with healthcare providers, and overall care quality [224]. Clinical outcomes, including readmission rates, infection rates, and survival rates, provide quantitative measures of care quality. Furthermore, continuity of care, which emphasizes coordinated services and consistent follow-ups, fosters long-term patient engagement and enhances healthcare outcomes [271].

Economic sustainability is a critical dimension of healthcare logistics. Metrics such as cost per patient, cost per diagnosis, and the cost-effectiveness of treatments are commonly used to evaluate financial performance [121, 127, 286]. These measures help identify opportunities to reallocate resources, maximizing value without compromising care quality. Cost minimization strategies often focus on reducing operational inefficiencies, such as excessive diagnostic testing or redundant administrative procedures, while maintaining high patient care standards.

Equity in healthcare operations ensures that services are accessible to diverse populations, regardless of socioeconomic, geographic, or demographic disparities [60, 211]. Metrics such as geographic accessibility, measured by average travel time to healthcare facilities, and socioeconomic accessibility, reflected in insurance coverage and affordability, are commonly used to evaluate equity [113]. Equity-focused metrics are particularly crucial in public health settings, where the equitable distribution of resources is essential to ensuring that vulnerable populations receive adequate care [76, 140].

In recent years, the sustainability of healthcare logistics has emerged as a critical performance criterion [150]. Metrics such as carbon footprint per patient, energy consumption of facilities, and waste management efficiency are increasingly being integrated into operational assessments [24, 27, 180]. Sustainability-oriented strategies, including green supply chains and energy-efficient facility design, play a pivotal role in enhancing the long-term viability of healthcare systems [215].

Resilience, defined as the ability of a healthcare system to adapt to disruptions, is another critical performance metric [287]. This criterion assesses the system's capacity to manage crises such as pandemics, natural disasters, or cyberattacks while maintaining core functions. Metrics such as recovery time following disruptions, supply chain adaptability, and surge capacity are commonly used to evaluate resilience [112, 152, 156, 195].

In practice, applying MCDM in healthcare logistics involves a comprehensive evaluation of these performance criteria. For instance, the Analytic Hierarchy Process (AHP) [247] can be utilized to assign relative weights to each criterion based on stakeholder priorities, facilitating balanced trade-offs between competing objectives. Similarly, techniques such as Data Envelopment Analysis (DEA) [81] and Goal Programming (GP) [165] offer structured frameworks for benchmarking performance against predefined standards and optimizing resource allocation under multiple constraints.

In conclusion, the performance criteria of operational healthcare reflect the intricate interplay between efficiency, patient satisfaction, financial viability, equity, sustainability, and resilience. These metrics serve as the foundation for MCDM frameworks, providing a structured approach to optimizing healthcare logistics and ensuring that systems remain responsive to evolving demands. Future research should prioritize the integration of real-time data analytics and advanced simulation tools to enhance the adaptability and precision of performance evaluations in dynamic healthcare environments.

3.2 Interconnectedness between Performance Criteria

The interconnectedness between performance criteria in operational healthcare logistics is a critical factor for effective decision-making and optimization. Healthcare logistics is inherently multidimensional, with performance criteria such as efficiency, cost-effectiveness, patient satisfaction, equity, and resilience being deeply interrelated. These relationships, often characterized by trade-offs and synergies, require careful analysis to achieve a balance that aligns with organizational and societal goals. Understanding these interdependencies is vital for implementing robust multicriteria decision-making (MCDM) frameworks.

Efficiency-focused metrics, such as minimizing patient wait times and optimizing resource utilization, often conflict with patient-centric measures like individualized care and satisfaction. For instance, reducing the average length of stay (ALOS) in hospitals to improve bed turnover might leave patients feeling rushed and dissatisfied with their care [15, 208]. Similarly, in emergency departments (EDs), prioritizing throughput can compromise the quality of consultations, negatively affecting clinical outcomes and patient satisfaction [250]. Balancing these objectives requires dynamic scheduling and simulation-based optimization models that integrate both operational and patient-centric variables.

Allocating healthcare resources equitably often involves higher costs due to the need to serve underserved regions or vulnerable populations [258, 260]. For example, ensuring equitable access to healthcare services might require establishing facilities in rural or low-income areas, where operational costs are higher because of logistical challenges and lower economies of scale [113]. Conversely, focusing solely on cost minimization risks exacerbating healthcare disparities. Multicriteria optimization models, such as Goal Programming (GP), enable decision-makers to assign weights to equity and cost objectives, facilitating a balanced allocation of resources [215].

The resilience of healthcare systems, particularly their ability to adapt to disruptions such as pandemics or natural disasters, often aligns with sustainability goals [31, 122, 228, 295]. For instance, investing in robust supply chains with diversified sourcing not only enhances resilience but also supports sustainability by promoting local suppliers and reducing carbon footprints [156]. Similarly, designing healthcare facilities with energy-efficient infrastructure contributes to both long-term resilience and environmental sustainability [268]. However, these synergies must be carefully evaluated within the context of budgetary constraints, as achieving both goals simultaneously may require substantial upfront investments.

Improving accessibility to healthcare services can significantly enhance clinical outcomes by enabling timely diagnosis and treatment. Metrics such as average travel time to healthcare facilities and appointment availability are strongly correlated with reduced mortality rates and improved chronic disease management [271]. However, increasing accessibility often requires service expansion, which can strain existing resources and affect operational efficiency. Techniques like the Analytic Network Process (ANP) are particularly effective for modeling such interdependencies, as they account for the bidirectional relationships between performance criteria [191, 247, 248].

The interconnectedness of performance criteria is further complicated by the involvement of multiple stakeholders, including patients, healthcare providers, policymakers, and administrators. Each group prioritizes different criteria based on their objectives. For example, patients may emphasize satisfaction and equity, while administrators might focus on cost efficiency and regulatory compliance. Multicriteria decision-making frameworks, such as ELECTRE [110, 111, 124] and TOPSIS [48, 218], are invaluable for aggregating these diverse preferences into a cohesive decision model, ensuring that all stakeholder priorities are adequately represented [125].

Healthcare systems are dynamic, with changes in one performance criterion often triggering feedback loops that impact others. For instance, improving patient satisfaction through better staffing ratios might initially increase costs but could result in long-term savings by reducing readmissions and malpractice claims [121, 127, 286]. Similarly, investments in technological infrastructure to enhance operational efficiency often yield cascading benefits, such as improved data analytics capabilities that support better resource allocation and patient care.

In summary, the interconnectedness between performance criteria in healthcare logistics underscores the importance of integrated decision-making approaches that account for the systemic impact of optimizing one metric on others. Advanced computational models and simulation-based methodologies are essential for capturing these relationships and generating actionable insights. As healthcare systems grow increasingly complex, understanding and managing these interdependencies will be critical to achieving sustainable and equitable healthcare outcomes.

3.3 Optimization from a Multicriteria Viewpoint

Optimization in healthcare logistics from a multicriteria perspective involves addressing the complex interplay of multiple, often conflicting objectives to achieve the best possible outcomes. Healthcare systems operate within intricate environments that require trade-offs among efficiency, cost, equity, resilience, and patient satisfaction. Multicriteria decision-making (MCDM) provides a systematic framework for navigating these trade-offs by employing advanced optimization models [71, 120, 143]. These models integrate diverse objectives into a unified decision-making process, balancing competing demands while accounting for operational constraints.

There are several needs for multicriteria optimization in healthcare logistics. Healthcare logistics encompasses diverse tasks, including facility location planning, inventory management, patient flow optimization, and resource allocation. Each of these functions has unique performance criteria that require optimization. For example, facility location models aim to maximize patient accessibility while minimizing transportation costs and operational expenses [13, 106, 108]. Similarly, resource allocation models must balance cost-efficiency with equity in healthcare service delivery. Multicriteria optimization frameworks address these competing objectives, prioritizing solutions that achieve a balance aligned with organizational goals. The need for multicriteria optimization in healthcare logistics arises from the diverse and often conflicting objectives that healthcare systems must address. Traditional single-objective optimization methods fail to capture the complexity of healthcare logistics, where trade-offs between competing criteria are unavoidable. Multicriteria optimization frameworks enable decision-makers to evaluate these trade-offs systematically and prioritize solutions aligned with organizational and societal goals. These frameworks also accommodate the involvement of multiple stakeholders, including patients, providers, and policymakers, each with unique priorities and perspectives [125].

Several optimization techniques are widely used in healthcare logistics to address the complexities of MCDM:

- Pareto Optimization: This approach identifies a set of Pareto-optimal solutions where improving one objective cannot occur without compromising another. Pareto frontiers are particularly valuable in healthcare logistics for visualizing trade-offs, such as balancing cost against patient satisfaction or timeliness against equity [89, 160].
- Weighted Sum Models (WSM): WSM assigns weights to different criteria based on their relative importance and aggregates them into a single objective function. This technique is widely used in problems such as staff rostering and inventory management, where explicit trade-offs between costs and service levels need to be addressed [29, 120].
- Goal Programming (GP): GP extends linear programming to address multiple, potentially conflicting objectives by establishing target goals for each criterion. This approach is particularly effective for resource allocation problems in hospitals, where specific benchmarks, such as patient wait times, staff satisfaction, and operational costs, must be achieved [166, 213, 244, 259].
- Analytic Hierarchy Process (AHP) and Analytic Network Process (ANP): These techniques utilize hierarchical or network structures to model complex decision-making problems. AHP is commonly applied in facility location decisions, helping to rank potential sites based on criteria such as accessibility, cost, and capacity [252]. ANP extends this approach by accounting for interdependencies among criteria [248].

Multicriteria optimization has been applied successfully across various domains in healthcare logistics:

- Emergency Medical Services (EMS): The routing of emergency vehicles is optimized using multiobjective models that balance criteria such as response time, fuel consumption, and route reliability. These models frequently integrate Geographic Information Systems (GIS) for spatial data analysis and decision support [101, 169, 179].
- Hospital Resource Allocation: Hospitals utilize multicriteria optimization to address challenges such as scheduling operating rooms, assigning nursing staff, and allocating intensive care unit (ICU) beds. For instance, a recent study applied goal programming to balance the allocation of ICU beds between COVID-19 and non-COVID-19 patients while minimizing resource wastage [21, 172, 291].

– Healthcare Supply Chain Management: Multicriteria optimization in healthcare supply chains addresses key factors such as inventory levels, transportation costs, and lead times [184]. Techniques like mixed-integer linear programming (MILP) have been applied to optimize the distribution of vaccines under conditions of uncertainty [77, 84, 88, 96].

Despite its benefits, multicriteria optimization in healthcare logistics faces several significant challenges. The dynamic and stochastic nature of healthcare systems introduces uncertainty into decision-making. For instance, demand for emergency services or ICU beds can fluctuate unpredictably, complicating the development of static optimization models. Additionally, the involvement of multiple stakeholders with divergent priorities makes assigning weights to criteria more complex. Furthermore, computational complexity increases as the number of criteria and constraints grows, necessitating the use of advanced algorithms and high-performance computing resources.

Emerging technologies, such as artificial intelligence (AI) and machine learning (ML), are transforming multicriteria optimization by enabling real-time decision-making and adaptability [231, 263]. For example, reinforcement learning models are being used to dynamically allocate resources in response to changing demand patterns, while deep learning algorithms enhance the predictive accuracy of demand forecasting models [4, 30, 226, 245]. These advancements hold significant potential to address traditional challenges in healthcare logistics and deliver more robust optimization solutions.

Future research in multicriteria optimization should prioritize integrating advanced simulation techniques and real-time data analytics to enhance decision-making precision. The adoption of digital twins (virtual replicas of healthcare systems) can enable scenario testing and optimization under simulated conditions [1, 83]. Moreover, ethical considerations, such as prioritizing patient equity and environmental sustainability as core objectives, should be emphasized in future optimization frameworks.

In conclusion, multicriteria optimization is a cornerstone of effective decision-making in healthcare logistics. By using advanced techniques such as Pareto optimization, goal programming, and artificial intelligence, healthcare systems can navigate complex trade-offs among competing objectives to deliver high-quality, equitable, and cost-efficient services. However, addressing challenges related to uncertainty, stakeholder diversity, and computational complexity will be essential for the continued advancement of this field.

4 Integration of OR tools in Healthcare IT and Interoperability

In this section, we explore the role of IT infrastructure in healthcare logistics. We highlight the importance of interoperability among various healthcare systems to ensure seamless communication and efficient data sharing. Additionally, we discuss the challenges associated with integrating logistics operations with electronic health records (EHRs) and other healthcare IT systems. This section addresses the horizontal integration between OR tools and Healthcare Information Technology (HIT), emphasizing how interoperability across digital systems enables data-driven coordination and real-time decision support in healthcare logistics.

The integration of OR tools into healthcare IT plays a fundamental role in enhancing the efficiency, responsiveness, and decision-making processes in healthcare logistics. OR tools, such as optimization algorithms and simulation models, significantly improve the efficiency of healthcare logistics by optimizing resource allocation, scheduling, and inventory management [38, 279, 296]. Digital platforms and real-time tracking systems enhance operational efficiency by providing accurate and timely information, which is crucial for effective decision-making [5, 39]. The use of OR techniques in HIT allows for agile responses to dynamic demands in healthcare logistics. This includes better management of patient flow, emergency services, and supply chain disruptions [39, 104, 190]. Real-time data analytics and predictive modeling enable healthcare providers to anticipate and respond to changes in patient needs and logistical challenges promptly [174]. The rapid advancements in HIT have led to the adoption of electronic health records (EHRs), predictive analytics, Internet of Things (IoT)-enabled monitoring systems, and artificial intelligence (AI)-driven decision support systems. However, the seamless incorporation of OR tools into HIT remains a challenge due to interoperability issues, data silos, and the complex nature of healthcare operations. The successful implementation of OR tools in HIT requires overcoming challenges such as data privacy, ethical considerations, and the need for collaboration among technologists, healthcare professionals, and policymakers [174].

Healthcare logistics is a data-intensive field that requires real-time data access, predictive insights, and robust optimization techniques to manage resources effectively. OR tools such as mathematical modeling, machine learning, heuristic optimization, and simulation are critical in optimizing facility location, resource allocation, inventory management, and supply chain operations. The integration of these tools with healthcare IT systems ensures that data-driven decisions are made efficiently, reducing costs and improving patient care quality [135, 136, 237].

In the following subsections, we discuss the role of interoperability in healthcare logistics, the application of predictive AI-driven analytics, and the importance of data management and IoT in enabling seamless communication across diverse healthcare IT systems.

4.1 Interoperability

Interoperability refers to the ability of healthcare IT systems to communicate, exchange, and utilize data effectively across different platforms and institutions [181, 232, 278]. The seamless flow of information is crucial for optimizing healthcare logistics, improving patient outcomes, and ensuring efficient resource allocation. Despite advancements in digital healthcare, achieving full interoperability remains a challenge due to differences in data standards, regulatory constraints, and fragmented healthcare IT ecosystems [153, 234].

Healthcare IT interoperability faces several persistent challenges that hinder seamless data exchange and the integration of analytical and optimization tools. One major issue lies in heterogeneous data standards, as healthcare institutions employ diverse data formats and communication protocols such as HL7, FHIR (Fast Healthcare Interoperability Resources), and DICOM, complicating interoperability across systems [50, 123, 261, 267]. Another critical challenge concerns data security and privacy, since healthcare data is highly sensitive and must comply with stringent regulations, including the Health Insurance Portability and Accountability Act (HIPAA) [202, 206] and the General Data Protection Regulation (GDPR) [16, 70, 116]. Furthermore, many institutions continue to rely on legacy systems, where outdated IT infrastructures hinder the adoption of modern interoperable solutions, leading to increased integration costs and technical complexity [119, 192, 242]. Finally, there is a lack of standardized implementation of operations research (OR) tools, which depend on structured and real-time data integration. The coexistence of multiple IT governance frameworks such as COBIT, ITIL, and ISO/IEC 27002 further complicates organizational decisions, as institutions often struggle to adapt these standards effectively to their specific operational and strategic needs [157, 214, 269].

Several solutions and approaches have been proposed to address interoperability challenges in healthcare IT. The adoption of standardized data exchange protocols, particularly the Fast Healthcare Interoperability Resources (FHIR), provides a structured foundation for consistent and efficient communication between healthcare systems. To further strengthen data security and reduce interoperability barriers, Blockchain technology has emerged as a promising solution, offering decentralized and tamper-resistant mechanisms for secure data sharing [41]. Additionally, cloud-based Healthcare as a Service (HaaS) platforms facilitate the integration of diverse IT systems, enabling scalability, accessibility, and real-time decision-making across healthcare networks [58, 200, 227]. Complementing these technological advancements, operations research-driven decision support systems (DSS) enhance interoperability by linking optimization models and analytical frameworks directly with electronic health records (EHRs) and healthcare supply chain databases, thereby improving operational efficiency, logistics management, and data-driven decision-making [131, 163, 289].

4.2 Predictive AI

Artificial intelligence (AI) is revolutionizing healthcare logistics by enabling predictive analytics, demand forecasting, and automated decision support systems. AI-driven OR models enhance decision-making in hospital resource planning, emergency response, and medical supply chain management [25, 170, 221, 239].

Artificial intelligence (AI) plays a transformative role in enhancing the efficiency, reliability, and responsiveness of healthcare IT systems. In demand forecasting, machine learning algorithms are employed to predict patient admission rates, allowing hospitals to optimize staff allocation and resource utilization [109, 146, 284]. Predictive maintenance in medical equipment is another critical application, where AI-based predictive analytics identify potential device failures in advance, ensuring timely maintenance and reducing costly equipment downtime [159, 264]. Furthermore, AI-driven supply chain optimization utilizes predictive modeling to analyze potential disruptions and facilitate proactive adjustments in inventory control and distribution networks, enhancing resilience against uncertainties such as pandemics [78, 154]. Lastly, personalized patient scheduling utilizes AI-assisted optimization to tailor appointment times, minimize waiting periods, and improve overall hospital workflow efficiency [277].

The adoption of artificial intelligence (AI) in healthcare IT faces several critical challenges that limit its widespread implementation and effectiveness. One major issue is data quality, as AI models depend on large volumes of high-quality, accurately labeled healthcare data to produce reliable and unbiased predictions [290]. Another concern involves regulatory and ethical compliance, since AI-driven decision-making must adhere to healthcare regulations, ensure algorithmic transparency, and mitigate biases that could negatively impact clinical outcomes [201]. Additionally, computational costs pose a significant barrier, as deploying AI-enhanced operations research (OR) tools demands substantial computational power and infrastructure, which can be financially prohibitive for smaller healthcare institutions [133, 203].

Future advancements in healthcare IT are expected to focus on enhancing transparency, privacy, and automation through the integration of advanced AI paradigms. The adoption of Explainable AI (XAI) techniques will be essential for improving the interpretability and trustworthiness of AI-driven decisions in healthcare logistics and operational planning [40]. Simultaneously, the development of federated learning frameworks will enable decentralized AI training on distributed healthcare datasets, ensuring model robustness while maintaining strict data privacy and compliance with regulatory standards [51]. Furthermore, the expansion of AI-driven robotic process automation (RPA) is anticipated to streamline hospital logistics and administrative workflows, reducing manual effort and improving overall operational efficiency [67].

4.3 Data Management and IoT

The increasing adoption of IoT in healthcare logistics enables real-time tracking of medical supplies, remote patient monitoring, and automated data collection. Efficient data management ensures that healthcare logistics operations remain responsive, scalable, and cost-effective [167].

The Internet of Things (IoT) plays a pivotal role in transforming healthcare IT by enabling real-time data collection, monitoring, and decision support across multiple operational domains. In smart inventory management, IoT sensors continuously track the status of medical inventories, helping reduce waste, prevent stockouts, and ensure the timely availability of essential medical supplies [75]. Through real-time patient monitoring, IoT-enabled wearable devices capture vital physiological data, allowing healthcare providers to remotely monitor patients with chronic conditions and deliver timely medical interventions [285]. Additionally, IoT contributes significantly to emergency response optimization, where sensor-driven tracking and communication systems enhance ambulance routing and coordination, thereby reducing response times and improving the overall efficiency of emergency medical services [197, 204, 229].

The implementation of Internet of Things (IoT) technologies in healthcare IT faces several key challenges that affect their scalability, security, and integration. Scalability issues arise as healthcare logistics increasingly rely on large-scale IoT networks, demanding robust data storage architectures and high-performance analytics frameworks to manage continuous data streams effectively. Cybersecurity threats represent another critical concern, since IoT-enabled healthcare systems are particularly vulnerable to cyberattacks and data breaches, necessitating the adoption of stringent encryption methods, authentication protocols, and network security measures. Furthermore, interoperability with existing IT infrastructures remains a major obstacle, as IoT devices must integrate seamlessly with electronic health records (EHRs) and decision support systems to ensure consistent data exchange, system compatibility, and optimal decision-making efficiency.

Emerging trends in IoT-driven healthcare logistics focus on enhancing responsiveness, security, and connectivity to support real-time decision-making and data integrity. Edge computing has gained prominence as a decentralized computing paradigm that processes data closer to its source, thereby reducing latency and improving the efficiency of real-time healthcare decisions. To address security and transparency concerns, blockchain-based frameworks are increasingly being integrated with IoT systems, providing immutable data records and secure transaction mechanisms that strengthen trust in healthcare data exchange [175]. Moreover, the advent of 5G-enabled healthcare IoT is revolutionizing connectivity by offering high-speed, low-latency communication, which facilitates real-time patient monitoring, predictive analytics, and optimized logistics management across distributed healthcare networks [26, 270].

The integration of OR tools in healthcare IT plays a crucial role in enhancing logistics efficiency, predictive decision-making, and seamless interoperability. Overcoming interoperability challenges through standardized data exchange, applying AI for predictive analytics, and utilizing IoT for real-time monitoring will be pivotal in shaping the future of healthcare logistics. As healthcare systems evolve, the adoption of these advanced technologies will be necessary to ensure optimal resource utilization, cost containment, and improved patient care outcomes.

5 Integration Across Different Time Scales and Uncertainty Levels

Building on the discussion in Section 4, which focused on horizontal integration through interoperability among healthcare IT systems, this section extends the perspective toward vertical integration across decision horizons. While horizontal integration ensures that electronic health records (EHRs), asset management, and logistics systems exchange data seamlessly to support real-time decision making, vertical integration aligns planning and control across multiple time scales.

We propose a four-level ordering scheme for planning tasks in healthcare logistics: *real-time* (H1), *operational* (H2), *tactical* (H3), and *strategic* (H4). Each horizon is defined by its cadence, decision scope, and uncertainty profile, and by the information it sends to and receives from adjacent horizons. Here, we extend the classification scheme of [148] by a real-time component. This scheme helps place problems (e.g., dispatching, rostering, contracting, network design) at the right level, choose suitable methods, and make hand-offs explicit so that short-term actions remain aligned with longer-term policy and design. Table 1 summarizes the horizons and their links.

Healthcare logistics decisions span these four linked horizons. Table 1 summarizes the decisions, methods, uncertainty treatments, and hand-offs for real-time (H1), operational (H2), tactical (H3), and strategic (H4) planning. Strategic and tactical layers set capacities, contracts, buffers, and targets, while operational and real-time layers translate these into executable schedules and reactive updates. Information flows upward as well: real-time and operational layers report usage, violations, and stress signals that trigger policy and design updates.

Table 1. Planning across time scales (H1–H4) with cadence included per horizon; columns list key decisions, methods, uncertainty treatment, and hand-offs

Horizon	Key decisions	Methods	Uncertainty treatment	Hand-offs / outputs
H1 Real-time (minutes–hours)	Dispatching, micro-rescheduling, and rerouting under arrivals, no-shows, traffic, and device failures.	Rolling-horizon re-optimization, learning-augmented heuristics, repair operators, and fast MILP subproblems.	Short-term forecasts with chance constraints, online updates, and safety filters.	Executable updates for tours and slots, KPIs such as lateness and cancellations to H2, and stress signals to H3.
H2 Operational (days–weeks)	Rosters, appointment books, daily tours, operating room and ICU blocks, and EMS or home-care shifts.	Multiobjective MILP, matheuristics, scenario sets, and chance constraints.	Scenario- or chance-based service-time, no-show, and travel variability with explicit buffer times.	Schedules and Pareto sets to H1, and resource usage and service KPIs to H3.
H3 Tactical (months)	Buffer stocks, reserve staffing, vendor contracts, coverage policies, and carbon or green constraints.	Multiobjective stochastic programs, distributionally robust optimization, and bilevel policy tuning.	DRO for non-stationary demand and lead times, sensitivity bands, and contingency policy sets.	Policy parameters to H2 (buffers and caps), risk budgets and equity targets to H2/H1, and requirements to H4.
H4 Strategic (years)	Network design, facility location, fleet and workforce sizing, and the HIT/ interoperability roadmap.	Robust location and network design, multi-period capacity planning, and portfolio decisions.	Deep uncertainty stress tests for pandemics, supply shocks, and cyber incidents via digital twins and scenario discovery.	Designs and capacities to H3, architectural and data standards to H1–H3, and long-horizon KPIs (equity and carbon) for governance.

Uncertainty changes with the horizon. Real-time control faces short-term variability such as arrivals, no-shows, traffic, and device failures; rolling-horizon re-optimization, learning-augmented heuristics, and safety filters keep systems responsive. Operational planning aggregates over days to weeks; scenario sets and chance constraints address service-time and travel-time variability, and explicit buffers protect service levels. Tactical planning must handle non-stationary demand and lead times; distributionally robust optimization (DRO) and sensitivity bands help policies remain stable under drift. Strategic planning addresses deep uncertainty from pandemics, supply shocks, and cyber incidents; digital twins and scenario discovery support stress testing and design choices.

Hand-offs must be explicit and machine-readable. Strategic design provides networks, capacities, and IT standards to the lower horizons. Tactical policy exports parameters such as buffers, caps, risk budgets, and equity targets to operational and real-time control. Operational planning delivers schedules and Pareto sets to real-time control. Real-time control issues executable updates and KPIs, and forwards stress indicators upward. Equity and carbon targets follow the same pattern: strategic targets, tactical budgets, operational enforcement, and real-time monitoring.

This structure enables closed-loop control. Streaming telemetry and KPIs from real-time operations guide short-term adjustments in operational planning and prompt tactical reviews. Repeated violations lead to revised buffers or contracts at the tactical layer and, if needed, changes in capacity or network design at the strategic layer. In this way, dispatching and micro-rescheduling stay aligned with rosters and blocks, which remain aligned with coverage policies and long-term capacity choices.

In this paper, *vertical integration* refers to aligning planning and control across time scales (H4–H1), including the upward and downward flow of targets, buffers, risk budgets, and performance signals. By contrast, *horizontal integration* refers to interoperability across peer healthcare IT and logistics systems at comparable decision levels, enabling consistent data capture, shared situational awareness, and the operationalization of OR recommendations within clinical and supply-chain workflows.

6 Conclusions and Future Perspectives

This position paper argues for a multiobjective and multidisciplinary view of healthcare logistics. We examined core OR problem classes, including timetabling, facility location, resource allocation, inventory, supply chains, and routing, and showed how equity, sustainability, patient outcomes, cost, and service must be treated as primary objectives or constraints rather than afterthoughts. Such a perspective requires not only methods that reveal trade-offs and alternatives but also governance that can elicit preferences from clinical, managerial, and public stakeholders and report impacts with the same discipline used for throughput or cost. Crucially, *horizontal integration* provides the data and execution substrate on which *vertical, time-scale-aware planning* can operate as a closed-loop system.

A second message is the need to fuse operations research with healthcare IT. Models only matter when they read reliable data and write executable outputs. Interoperability-by-design across EHR, asset and inventory systems, laboratory and imaging systems, and supplier interfaces is therefore a prerequisite. Standardized schemas and APIs, lineage and validation tool-chains, and continuous data quality checks should be coupled to optimization inputs and outputs. With this foundation, predictive analytics, AI, and IoT can deliver timely forecasts and state estimates while optimization produces schedules, policies, and alerts that downstream systems can enact.

Third, planning must be coherent across time scales and uncertainty profiles. We propose the H1–H4 ordering scheme as a practical backbone for assigning tasks, methods, and hand-offs: real-time (H1), operational (H2), tactical (H3), and strategic (H4). Table 1 summarizes decisions, methods, uncertainty treatments, and artifacts exchanged at each horizon. H4 and H3 set designs, capacities, buffers, and budgets (including equity and carbon targets); H2 converts them into executable schedules; H1 adapts in minutes to hours. Information flows upward: H1/H2 provide KPIs, violations, and stress signals; H3/H4 update policies and designs. Method choices should match horizon and uncertainty: fast repairs and rolling-horizon MILP at H1; multiobjective MILP and matheuristics with scenarios or chance constraints at H2; stochastic and distributionally robust programs with sensitivity bands at H3; and robust, multi-period network and capacity planning with stress tests and digital twins at H4. Treating uncertainty as drifting rather than fixed, using online learning and Bayesian updating, keeps policies effective as conditions change.

We propose a research agenda aligned with these three themes. First, advanced multiobjective modeling that puts equity and sustainability on equal footing with cost and service, with explainable outputs that expose trade-offs and support contestability. Second, deliver interoperability-by-design: FHIR-first data access; portable optimization artifacts; machine-readable hand-offs across H1–H4; and monitoring that ties data quality to decision quality. Third, develop time-scale-aware optimization that is both robust and adaptive: learning-augmented dispatch for H1; schedule design with scenario/chance guarantees for H2; distributionally robust policy setting and contract design for H3; and stress-tested strategic planning for H4 using digital twins. Progress in computation, including decomposition, matheuristics, parallel evolutionary multicriterion optimization (EMO), and hardware-aware implementations on GPU and edge platforms, will reduce latency and expand deployment. Community benchmarks with privacy-preserving data and standardized H1–H4 artifacts will strengthen reproducibility and accelerate translation to practice.

Overall, a healthcare logistics stack that is multiobjective, interoperable, and time-scale-aware can turn streaming data into reliable action while meeting equity and sustainability targets. The path forward is clear: develop shared data and model pipelines, align methods with temporal horizons and uncertainty levels, and assess outcomes with the same rigor applied to cost and capacity evaluations.

Declarations

Competing Interests: The authors have no competing interests to declare that are relevant to the content of this paper.

References

1. Abd Elaziz, M., Al-qaness, M.A., Dahou, A., Al-Betar, M.A., Mohamed, M.M., El-Shinawi, M., Ali, A., Ewees, A.A.: Digital twins in healthcare: Applications, technologies, simulations, and future trends. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery **14**(6), e1559 (2024)

2. Abd Rahim, K.N.K., Lattepi, N.M., Sarimin, R., Foo, S.S., Akmal, S., Lee, S.W., Ghazali, I.M.M.: Development of an multicriteria decision analysis framework for rare disease reimbursement prioritization in malaysia. International Journal of Technology Assessment in Health Care **40**(1), e35 (2024)
3. Abdalkareem, Z.A., Amir, A., Al-Betar, M.A., Ekhan, P., Hammouri, A.I.: Healthcare scheduling in optimization context: a review. Health and Technology **11**, 445–469 (2021)
4. Abdellatif, A.A., Mhaisen, N., Mohamed, A., Erbad, A., Guizani, M.: Reinforcement learning for intelligent healthcare systems: A review of challenges, applications, and open research issues. IEEE Internet of Things Journal **10**(24), 21,982–22,007 (2023)
5. Adebayo, A., Ogunnaike, O., Inegbedion, D., et al.: Information management role in logistics operations: optimization of distribution process in medical supply stores in lagos state. Brazilian Journal of Operations & Production Management **20**(2), 1394–1394 (2023)
6. Adil, M., Ali, J., Jadoon, M.M., Alotaibi, S.R., Kumar, N., Farouk, A., Song, H.: Covid-19: Secure healthcare internet of things networks, current trends and challenges with future research directions. ACM Transactions on Sensor Networks **19**(3), 1–25 (2023)
7. Afshari, H., Peng, Q.: Challenges and solutions for location of healthcare facilities. Industrial Engineering and Management **3**(2), 1–12 (2014)
8. Ageron, B., Benzidia, S., Bourlakis, M.: Healthcare logistics and supply chain–issues and future challenges. Supply Chain Forum: An International Journal **19**(1), 1–3 (2018)
9. Agrebi, M., Abed, M., Omri, M.N.: ELECTRE I Based Relevance Decision-Makers Feedback to the Location Selection of Distribution Centers. Journal of Advanced Transportation **2017**(1), 7131,094 (2017)
10. Ahmadi, E., Mosadegh, H., Maihami, R., Ghalehkhondabi, I., Sun, M., Süer, G.A.: Intelligent inventory management approaches for perishable pharmaceutical products in a healthcare supply chain. Computers & Operations Research **147**, 105,968 (2022)
11. Ahmadi, H., Arji, G., Shahmoradi, L., Safdari, R., Nilashi, M., Alizadeh, M.: The application of internet of things in healthcare: a systematic literature review and classification. Universal Access in the Information Society **18**, 837–869 (2019)
12. Ahmadi-Javid, A., Jalali, Z., Klassen, K.J.: Outpatient appointment systems in healthcare: A review of optimization studies. European Journal of Operational Research **258**(1), 3–34 (2017)
13. Ahmadi-Javid, A., Seyedi, P., Syam, S.S.: A survey of healthcare facility location. Computers & Operations Research **79**, 223–263 (2017)
14. Ahsan, K.B., Alam, M., Morel, D.G., Karim, M.: Emergency department resource optimisation for improved performance: a review. Journal of Industrial Engineering International **15**(Suppl 1), 253–266 (2019)
15. Akcali, E., Côté, M.J., Lin, C.: A network flow approach to optimizing hospital bed capacity decisions. Health Care Management Science **9**, 391–404 (2006)
16. Al Khatib, I., Ahmed, N., Ndyiaye, M.: GDPR Compliance of Hospital Management Systems in the UAE. Journal of Data Science and Intelligent Systems (2024)
17. Ala, A., Chen, F.: Appointment scheduling problem in complexity systems of the healthcare services: A comprehensive review. Journal of Healthcare Engineering **2022**(1), 5819,813 (2022)
18. Ala, A., Goli, A., Mirjalili, S., Simic, V.: A fuzzy multi-objective optimization model for sustainable healthcare supply chain network design. Applied Soft Computing **150**, 111,012 (2024)
19. Ala, A., Simic, V., Deveci, M., Pamucar, D.: Simulation-based analysis of appointment scheduling system in healthcare services: a critical review. Archives of Computational Methods in Engineering **30**(3), 1961–1978 (2023)

20. Alazab, M., Khan, L.U., Koppu, S., Ramu, S.P., Iyapparaja, M., Boobalan, P., Baker, T., Maddikunta, P.K.R., Gadekallu, T.R., Aljuhani, A.: Digital twins for healthcare 4.0—recent advances, architecture, and open challenges. IEEE Consumer Electronics Magazine **12**(6), 29–37 (2022)
21. Alban, A., Chick, S.E., Dongelmans, D.A., Vlaar, A.P., Sent, D.: Icu capacity management during the covid-19 pandemic using a process simulation. Intensive care medicine **46**(8), 1624–1626 (2020)
22. Ali, H.H., Lamsali, H., Othman, S.N.: Hospital scheduling analysis: a contemporary review and proposed schematic understanding. Jour of Adv Research in Dynamical & Control Systems **10**(6) (2018)
23. Alimohammadlou, M., Khoshsepehr, Z.: Green-resilient supplier selection: a hesitant fuzzy multi-criteria decision-making model. Environment, Development and Sustainability pp. 1–37 (2022)
24. AlJaberi, O.A., Hussain, M., Drake, P.R.: A framework for measuring sustainability in healthcare systems. International Journal of Healthcare Management (2020)
25. Alnsour, Y., Johnson, M., Albizri, A., Harfouche, A.H.: Predicting patient length of stay using artificial intelligence to assist healthcare professionals in resource planning and scheduling decisions. Journal of Global Information Management (JGIM) **31**(1), 1–14 (2023)
26. Alshammari, N., Sarker, M.N.I., Kamruzzaman, M., Alruwaili, M., Alanazi, S.A., Raihan, M.L., AlQahtani, S.A.: Technology-driven 5G enabled e-healthcare system during COVID-19 pandemic. IET Communications **16**(5), 449–463 (2022)
27. Alshqaqeeq, F., Esmaeili, M.A., Overcash, M., Twomey, J.: Quantifying hospital services by carbon footprint: a systematic literature review of patient care alternatives. Resources, Conservation and Recycling **154**, 104,560 (2020)
28. Anderson, R.M.: Stochastic models and data driven simulations for healthcare operations. Ph.D. thesis, Massachusetts Institute of Technology (2014)
29. Angelis, A., Kanavos, P., Montibeller, G.: Resource allocation and priority setting in health care: a multi-criteria decision analysis problem of value? Global Policy **8**, 76–83 (2017)
30. Angula, T.N., Dongo, A.: Assessing the impact of artificial intelligence and machine learning on forecasting medication demand and supply in public pharmaceutical systems: a systematic review. GSC Biological and Pharmaceutical Sciences **26**(2), 140–150 (2024)
31. Arsenault, C., Gage, A., Kim, M.K., Kapoor, N.R., Akweongo, P., Amponsah, F., Aryal, A., Asai, D., Awoonor-Williams, J.K., Ayele, W., et al.: COVID-19 and resilience of healthcare systems in ten countries. Nature medicine **28**(6), 1314–1324 (2022)
32. de Assis, A.G., Dos Santos, A.F.A., Dos Santos, L.A., da Costa, J.F., Cabral, M.A.L., de Souza, R.P.: Classification of medicines and materials in hospital inventory management: a multi-criteria analysis. BMC Medical Informatics and Decision Making **22**(1), 325 (2022)
33. Atta, S.: An improved harmony search algorithm using opposition-based learning and local search for solving the maximal covering location problem. Engineering Optimization **56**(8), 1298–1317 (2024)
34. Atta, S., Basto-Fernandes, V., Emmerich, M.: A concise review of the home health care routing and scheduling problem. Operations Research Perspectives **15**, 100,347 (2025)
35. Atta, S., Mahapatra, P.R.S., Mukhopadhyay, A.: A multi-objective formulation of maximal covering location problem with customers' preferences: Exploring pareto optimality-based solutions. Expert Systems with Applications **186**, 115,830 (2021)
36. Atta, S., Sinha Mahapatra, P.R., Mukhopadhyay, A.: Solving maximal covering location problem using genetic algorithm with local refinement. Soft Computing **22**, 3891–3906 (2018)
37. Atta, S., Sinha Mahapatra, P.R., Mukhopadhyay, A.: Multi-objective uncapacitated facility location problem with customers' preferences: Pareto-based and weighted sum ga-based approaches: S. atta et al. Soft Computing **23**(23), 12,347–12,362 (2019)

38. Atuahene, I., Kubi, P.A., Acosta-Amando, R., Lacera-Cortes, I., Sawhney, R., Atuahene, E., Upreti, G.: Towards an operations research sustainable healthcare: an overview of recent applications of or in healthcare. In: IIE Annual Conference. Proceedings, p. 2810. Institute of Industrial and Systems Engineers (IISE) (2014)
39. Avinash, B., Joseph, G.: Reimagining healthcare supply chains: a systematic review on digital transformation with specific focus on efficiency, transparency and responsiveness. Journal of Health Organization and Management **38**(8), 1255–1279 (2024)
40. Ayesha, A., Ahamed, N.N.: Explainable artificial intelligence (eai): For healthcare applications and improvements. In: Explainable Artificial Intelligence for Biomedical and Healthcare Applications, pp. 162–196. CRC Press (2024)
41. Azaria, A., Ekblaw, A., Vieira, T., Lippman, A.: MedRec: Using Blockchain for Medical Data Access and Permission Management. In: 2016 2nd international conference on open and big data (OBD), pp. 25–30. IEEE (2016)
42. Badejo, O., Ierapetritou, M.: Enhancing pharmaceutical supply chain resilience: A multi-objective study with disruption management. Computers & Chemical Engineering **188**, 108,769 (2024)
43. Bailey, K., Tucker, R., Blair, J.: Resource allocation and management for healthcare facilities. In: Emergency Management for Healthcare Leaders, pp. 80–86. Productivity Press (2025)
44. Baltussen, R., Niessen, L.: Priority setting of health interventions: the need for multi-criteria decision analysis. Cost effectiveness and resource allocation **4**, 1–9 (2006)
45. Banasik, A., Bloemhof-Ruwaard, J.M., Kanellopoulos, A., Claassen, G., van der Vorst, J.G.: Multi-criteria decision making approaches for green supply chains: A review. Flexible Services and Manufacturing Journal **30**, 366–396 (2018)
46. Barbosa, E., Gonçalves, A., Guerra, M., Cruz, C.: A systematic review on resource allocation in public health. European Journal of Public Health **30**(Supplement_5), ckaa166–1309 (2020)
47. Beheshtifar, S., Alimoahmmadi, A.: A multiobjective optimization approach for location-allocation of clinics. International Transactions in Operational Research **22**(2), 313–328 (2015)
48. Behzadian, M., Otaghsara, S.K., Yazdani, M., Ignatius, J.: A state-of the-art survey of topsis applications. Expert Systems with Applications **39**(17), 13,051–13,069 (2012)
49. Belton, V., Stewart, T.: Multiple criteria decision analysis: an integrated approach. Springer Science & Business Media (2012)
50. Bender, D., Sartipi, K.: HL7 FHIR: An Agile and RESTful approach to healthcare information exchange. In: Proceedings of the 26th IEEE international symposium on computer-based medical systems, pp. 326–331. IEEE (2013)
51. Bhargava, S., Gupta, D., Gururaj, H.: Opportunities and challenges in federated learning. Federated Learning Techniques and Its Application in the Healthcare Industry pp. 191–206 (2024)
52. Bhattacharya, A., Geraghty, J., Young, P.: Supplier selection paradigm: An integrated hierarchical qfd methodology under multiple-criteria environment. Applied Soft Computing **10**(4), 1013–1027 (2010)
53. Birje, M.N., Hanji, S.S.: Internet of things based distributed healthcare systems: a review. Journal of Data, Information and Management **2**(3), 149–165 (2020)
54. Blanchard, D.: Supply chain management best practices. John Wiley & Sons (2021)
55. Booker, L.A., Mills, J., Bish, M., Spong, J., Deacon-Crouch, M., Skinner, T.C.: Nurse rostering: understanding the current shift work scheduling processes, benefits, limitations, and potential fatigue risks. BMC nursing **23**(1), 295 (2024)
56. Bose, D.C.: Inventory management. PHI Learning Pvt. Ltd. (2006)
57. Boutilier, J.J., Chan, T.C.: Ambulance emergency response optimization in developing countries. Operations Research **68**(5), 1315–1334 (2020)

58. Boyce, A., Dacey, M., Bashford, T.: An effective approach for extending medical data to the cloud through synthetic data generation for educational environments. In: Digital Professionalism in Health and Care: Developing the Workforce, Building the Future, pp. 147–151. IOS Press (2022)
59. Božić, D., Šego, D., Stanković, R., Šafran, M.: Logistics in healthcare: a selected review of literature from 2010 to 2022. Transportation Research Procedia **64**, 288–298 (2022)
60. Bradley, B.D., Jung, T., Tandon-Verma, A., Khoury, B., Chan, T.C., Cheng, Y.L.: Operations research in global health: a scoping review with a focus on the themes of health equity and impact. Health research policy and systems **15**, 1–24 (2017)
61. Brans, J.P., Mareschal, B., Figueira, J., Greco, S., et al.: Multiple criteria decision analysis: state of the art surveys. International Series in Operations Research & Management Science **78**, 163–186 (2005)
62. Braunstein, M.L.: Healthcare in the age of interoperability: the promise of fast healthcare interoperability resources. IEEE pulse **9**(6), 24–27 (2018)
63. Braveman, P., Egerter, S., Williams, D.R.: The social determinants of health: coming of age. Annual review of public health **32**(1), 381–398 (2011)
64. Bruno, G., Giannikos, I.: Location and gis. Location science pp. 509–536 (2015)
65. Burdett, R.L., Corry, P., Yarlagadda, P., Cook, D., Birgan, S.: The efficacy of utility functions for multicriteria hospital case-mix planning. International Transactions in Operational Research **31**(2), 807–862 (2024)
66. Burke, E., De Causmaecker, P., Vanden Berghe, G.: A hybrid tabu search algorithm for the nurse rostering problem. In: Simulated Evolution and Learning: Second Asia-Pacific Conference on Simulated Evolution and Learning, SEAL'98 Canberra, Australia, November 24–27, 1998 Selected Papers 2, pp. 187–194. Springer (1999)
67. Caccavale, R., Finzi, A.: An Automated Guided Vehicle for Flexible and Interactive Task Execution in Hospital Scenarios. In: Artificial Intelligence and Robotics (AIRO 2019), pp. 39–46 (2019)
68. Cardoen, B., Demeulemeester, E.: Capacity of clinical pathways—a strategic multi-level evaluation tool. Journal of Medical Systems **32**, 443–452 (2008)
69. Cardoen, B., Demeulemeester, E., Beliën, J.: Operating room planning and scheduling: A literature review. European journal of operational research **201**(3), 921–932 (2010)
70. Chakraborti, T.: Data protection, information security and international data transfers: A practical guide through key provisions and compliance tools. In: HEALTHTECH, pp. 24–52. Edward Elgar Publishing (2020)
71. Chakraborty, S., Raut, R.D., Rofin, T., Chakraborty, S.: A comprehensive and systematic review of multi-criteria decision-making methods and applications in healthcare. Healthcare Analytics p. 100232 (2023)
72. Chan, H.K., Yin, S., Chan, F.T.: Implementing just-in-time philosophy to reverse logistics systems: a review. International Journal of Production Research **48**(21), 6293–6313 (2010)
73. Chauhan, A., Singh, A.: A hybrid multi-criteria decision making method approach for selecting a sustainable location of healthcare waste disposal facility. Journal of Cleaner Production **139**, 1001–1010 (2016)
74. Chen, T.L., Wang, C.: Multi-objective simulation optimization for medical capacity allocation in emergency department. Journal of Simulation **10**(1), 50–68 (2016)
75. Chinthakuntla Vignesh, R.: Developing efficient methods for tracking the location, status, and maintenance needs of oxygen cylinders equipped with iot devices. In: Proceedings of the International Conference on Internet of Everything and Quantum Information Processing, vol. 1029, p. 170. Springer Nature (2024)
76. Chisolm, D.J., Dugan, J.A., Figueroa, J.F., Lane-Fall, M.B., Roby, D.H., Rodriguez, H.P., Ortega, A.N.: Improving health equity through health care systems research. Health services research **58**, 289–299 (2023)

77. Chowdhury, N.R., Ahmed, M., Mahmud, P., Paul, S.K., Liza, S.A.: Modeling a sustainable vaccine supply chain for a healthcare system. Journal of Cleaner Production **370**, 133,423 (2022)
78. Chowdhury, P., Paul, S.K., Kaisar, S., Moktadir, M.A.: Covid-19 pandemic related supply chain studies: A systematic review. Transportation Research Part E: Logistics and Transportation Review **148**, 102,271 (2021)
79. Church, R.L.: Location modelling and gis. Geographical information systems **1**, 293–303 (1999)
80. Church, R.L., Murray, A.T.: Business site selection, location analysis, and GIS. John Wiley & Sons Hoboken, NJ (2009)
81. Cook, W.D., Seiford, L.M.: Data envelopment analysis (dea)–thirty years on. European journal of operational research **192**(1), 1–17 (2009)
82. Créput, J.C., Hajjam, A., Koukam, A., Kuhn, O.: Dynamic vehicle routing problem for medical emergency management. In: Self Organizing Maps-Applications and Novel Algorithm Design, pp. 233–250. IntechOpen (2011)
83. Croatti, A., Gabellini, M., Montagna, S., Ricci, A.: On the integration of agents and digital twins in healthcare. Journal of Medical Systems **44**(9), 161 (2020)
84. Cuevas-Lopez, J.J., Azzaro-Pantel, C., Almaraz, S.D.L.: Multi-objective optimization for pharmaceutical supply chain design: application to covid-19 vaccine distribution network. In: Computer Aided Chemical Engineering, vol. 53, pp. 679–684. Elsevier (2024)
85. Current, J., Daskin, M., Schilling, D., et al.: Discrete network location models. Facility location: Applications and theory **1**, 81–118 (2002)
86. Dantas, L.F., Fleck, J.L., Oliveira, F.L.C., Hamacher, S.: No-shows in appointment scheduling–a systematic literature review. Health Policy **122**(4), 412–421 (2018)
87. Daskin, M.: Network and discrete location: models, algorithms and applications. Journal of the Operational Research Society **48**(7), 763–764 (1997)
88. De Boeck, K., Decouttere, C., Vandaele, N.: Vaccine distribution chains in low-and middle-income countries: A literature review. Omega **97**, 102,097 (2020)
89. Deb, K., Pratap, A., Agarwal, S., Meyarivan, T.: A fast and elitist multiobjective genetic algorithm: Nsga-ii. IEEE Transactions on Evolutionary Computation **6**(2), 182–197 (2002)
90. Deb, K., Sindhya, K., Hakanen, J.: Multi-objective optimization. In: Decision sciences, pp. 161–200. CRC Press (2016)
91. Dell'Ovo, M., Capolongo, S., Oppio, A.: Combining spatial analysis with mcda for the siting of healthcare facilities. Land use policy **76**, 634–644 (2018)
92. Dell'Ovo, M., Frej, E.A., Oppio, A., Capolongo, S., Morais, D.C., de Almeida, A.T.: FITradeoff method for the location of healthcare facilities based on multiple stakeholders' preferences. In: Group Decision and Negotiation in an Uncertain World: 18th International Conference, GDN 2018, Nanjing, China, June 9-13, 2018, Proceedings 18, pp. 97–112. Springer (2018)
93. Dhingra, S., Raut, R., Naik, K., Muduli, K.: Blockchain technology applications in healthcare supply chains–a review. IEEE Access (2024)
94. Diaby, V., Campbell, K., Goeree, R.: Multi-criteria decision analysis (mcda) in health care: a bibliometric analysis. Operations research for health care **2**(1-2), 20–24 (2013)
95. Drezner, Z., Hamacher, H.W.: Facility location: applications and theory. Springer Science & Business Media (2004)
96. Duijzer, L.E., Van Jaarsveld, W., Dekker, R.: Literature review: The vaccine supply chain. European Journal of Operational Research **268**(1), 174–192 (2018)
97. Eiselt, H.A., Sandblom, C.L.: Decision analysis, location models, and scheduling problems. Springer Science & Business Media (2013)
98. El Morr, C., Ali-Hassan, H.: Analytics in healthcare: a practical introduction. Springer (2019)

99. Erhard, M., Schoenfelder, J., Fügener, A., Brunner, J.O.: State of the art in physician scheduling. European Journal of Operational Research **265**(1), 1–18 (2018)
100. Ernst, A.T., Jiang, H., Krishnamoorthy, M., Sier, D.: Staff scheduling and rostering: A review of applications, methods and models. European journal of operational research **153**(1), 3–27 (2004)
101. Esmaelian, M., Tavana, M., Santos Arteaga, F.J., Mohammadi, S.: A multicriteria spatial decision support system for solving emergency service station location problems. International Journal of Geographical Information Science **29**(7), 1187–1213 (2015)
102. Fahimnia, B., Jabbarzadeh, A., Sarkis, J.: Greening versus resilience: A supply chain design perspective. Transportation Research Part E: Logistics and Transportation Review **119**, 129–148 (2018)
103. Fahrni, M.L., Ismail, I.A.N., Refi, D.M., Almeman, A., Yaakob, N.C., Saman, K.M., Mansor, N.F., Noordin, N., Babar, Z.U.D.: Management of covid-19 vaccines cold chain logistics: a scoping review. Journal of Pharmaceutical Policy and Practice **15**(1), 16 (2022)
104. Fakhimi, M., Mustafee, N.: Application of operations research within the UK healthcare context. In: 2012 Operational Research Society Simulation Workshop, SW 2012, pp. 66–82 (2012)
105. Fang, L., Li, H.: Multi-criteria decision analysis for efficient location-allocation problem combining dea and goal programming. RAIRO-operations research-recherche opérationnelle **49**(4), 753–772 (2015)
106. Farahani, R.Z., Asgari, N., Heidari, N., Hosseininia, M., Goh, M.: Covering problems in facility location: A review. Computers & Industrial Engineering **62**(1), 368–407 (2012)
107. Farahani, R.Z., Hekmatfar, M.: Facility location: concepts, models, algorithms and case studies. Springer Science & Business Media (2009)
108. Farahani, R.Z., SteadieSeifi, M., Asgari, N.: Multiple criteria facility location problems: A survey. Applied mathematical modelling **34**(7), 1689–1709 (2010)
109. Feretzakis, G., Sakagianni, A., Anastasiou, A., Kapogianni, I., Tsoni, R., Koufopoulou, C., Karapiperis, D., Kaldis, V., Kalles, D., Verykios, V.S.: Machine learning in medical triage: A predictive model for emergency department disposition. Applied Sciences **14**(15), 6623 (2024)
110. Figueira, J.R., Greco, S., Roy, B., Słowiński, R.: ELECTRE methods: Main features and recent developments. Handbook of multicriteria analysis pp. 51–89 (2010)
111. Figueira, J.R., Greco, S., Roy, B., Słowiński, R.: An overview of ELECTRE methods and their recent extensions. Journal of Multi-Criteria Decision Analysis **20**(1-2), 61–85 (2013)
112. Fleming, P., O'Donoghue, C., Almirall-Sanchez, A., Mockler, D., Keegan, C., Cylus, J., Sagan, A., Thomas, S.: Metrics and indicators used to assess health system resilience in response to shocks to health systems in high income countries—a systematic review. Health Policy **126**(12), 1195–1205 (2022)
113. Frohlich, K.L., Abel, T.: Environmental justice and health practices: understanding how health inequities arise at the local level. From Health Behaviours to Health Practices pp. 43–56 (2014)
114. Fuller, A., Fan, Z., Day, C., Barlow, C.: Digital twin: Enabling technologies, challenges and open research. IEEE access **8**, 108,952–108,971 (2020)
115. Gaynor, M., Yu, F., Andrus, C.H., Bradner, S., Rawn, J.: A general framework for interoperability with applications to healthcare. Health Policy and Technology **3**(1), 3–12 (2014)
116. Georgiou, D., Lambrinoudakis, C.: Compatibility of a security policy for a cloud-based healthcare system with the EU general data protection regulation (GDPR). Information **11**(12), 586 (2020)
117. Getele, G.K., Li, T., Arrive, J.T.: The role of supply chain management in healthcare service quality. IEEE Engineering Management Review **48**(1), 145–155 (2020)

118. Ghafour, K.: Multi-objective continuous review inventory policy using MOPSO and TOPSIS methods. Computers & Operations Research **163**, 106,512 (2024)
119. Gibbs, C., Lohmann, D., Liu, C.R., Coady, Y.: Modular integration through aspects: Making cents of legacy systems. In: 2007 40th Annual Hawaii International Conference on System Sciences (HICSS'07), pp. 132–132. IEEE (2007)
120. Glaize, A., Duenas, A., Di Martinelly, C., Fagnot, I.: Healthcare decision-making applications using multicriteria decision analysis: A scoping review. Journal of Multi-Criteria Decision Analysis **26**(1-2), 62–83 (2019)
121. Gold, M.R.: Cost-effectiveness in health and medicine. Oxford University Press (1996)
122. Goodarzian, F., Ghasemi, P., Gunasekaren, A., Taleizadeh, A.A., Abraham, A.: A sustainable-resilience healthcare network for handling COVID-19 pandemic. Annals of Operations Research pp. 1–65 (2022)
123. Gottumukkala, M., El-Gayar, O., Noteboom, C.B.: Interoperability in Healthcare using FHIR: A Systematic Literature Review. In: AMCIS 2022 TREOs, 65 (2022). URL https://aisel.aisnet.org/treos_amcis2022/65
124. Govindan, K., Jepsen, M.B.: ELECTRE: A comprehensive literature review on methodologies and applications. European Journal of Operational Research **250**(1), 1–29 (2016)
125. Govindan, K., Soleimani, H., Kannan, D.: Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future. European Journal of Operational Research **240**(3), 603–626 (2015)
126. Goyal, S., Sharma, N., Bhushan, B., Shankar, A., Sagayam, M.: Iot enabled technology in secured healthcare: applications, challenges and future directions. Cognitive Internet of Medical Things for Smart Healthcare: Services and Applications pp. 25–48 (2021)
127. Gray, A.M., Clarke, P.M., Wolstenholme, J.L., Wordsworth, S.: Applied methods of cost-effectiveness analysis in healthcare, vol. 3. OUP Oxford (2010)
128. Green, L.V., Savin, S.: Reducing delays for medical appointments: A queueing approach. Operations Research **56**(6), 1526–1538 (2008)
129. Green, L.V., Savin, S., Wang, B.: Managing patient service in a diagnostic medical facility. Operations Research **54**(1), 11–25 (2006)
130. Gualandi, R., Masella, C., Tartaglini, D.: Improving hospital patient flow: a systematic review. Business process management journal **26**(6), 1541–1575 (2020)
131. Guardia, A.: Decision support: time for collaboration. Yearbook of Medical Informatics **6**(1), 102 – 104 (2011). DOI 10.1055/s-0038-1638746
132. Guerriero, F., Guido, R.: Operational research in the management of the operating theatre: a survey. Health care management science **14**, 89–114 (2011)
133. Guetibi, S.: Integrating artificial intelligence with information systems in healthcare supply chain management. In: Modern Artificial Intelligence and Data Science 2024: Tools, Techniques and Systems, pp. 367–374. Springer (2024)
134. Guindo, L.A., Wagner, M., Baltussen, R., Rindress, D., van Til, J., Kind, P., Goetghebeur, M.M.: From efficacy to equity: Literature review of decision criteria for resource allocation and healthcare decisionmaking. Cost effectiveness and resource allocation **10**, 1–13 (2012)
135. Gunal, M.M.: A guide for building hospital simulation models. Health Systems **1**(1), 17–25 (2012)
136. Gunal, M.M.: Simulation methods for improving healthcare services: Considerations for modelling. In: International Conference on Simulation and Modeling Methodologies, Technologies and Applications, pp. 1–8. Springer (2023)
137. Gupta, A., Maranas, C.D.: Managing demand uncertainty in supply chain planning. Computers & Chemical Engineering **27**(8-9), 1219–1227 (2003)
138. Gupta, D., Denton, B.: Appointment scheduling in health care: Challenges and opportunities. IIE transactions **40**(9), 800–819 (2008)

139. Gurumurthy, P.: Dynamic Stochastic Vehicle Routing Model in Home Healthcare Scheduling. University of Missouri-Columbia (2004)
140. Gustafson, P., Abdul Aziz, Y., Lambert, M., Bartholomew, K., Rankin, N., Fusheini, A., Brown, R., Carswell, P., Ratima, M., Priest, P., et al.: A scoping review of equity-focused implementation theories, models and frameworks in healthcare and their application in addressing ethnicity-related health inequities. Implementation Science **18**(1), 51 (2023)
141. Haas, E.J., Casey, M.L., Furek, A., Aldrich, K., Ragsdale, T., Crosswy, S., Moore, S.M.: Lessons learned from the development and demonstration of a ppe inventory monitoring system for us hospitals. Health Security **19**(6), 582–591 (2021)
142. Hakimi, S.L.: Optimum locations of switching centers and the absolute centers and medians of a graph. Operations research **12**(3), 450–459 (1964)
143. Hansen, P., Devlin, N.: Multi-criteria decision analysis (MCDA) in healthcare decision-making. In: Oxford research encyclopedia of economics and finance. Oxford University Press (2019)
144. Harper, P.R., Powell, N., Williams, J.E.: Modelling the size and skill-mix of hospital nursing teams. Journal of the Operational Research Society **61**(5), 768–779 (2010)
145. Haszlinna Mustaffa, N., Potter, A.: Healthcare supply chain management in malaysia: a case study. Supply chain management: an international journal **14**(3), 234–243 (2009)
146. Hatachi, T., Hashizume, T., Taniguchi, M., Inata, Y., Aoki, Y., Kawamura, A., Takeuchi, M.: Machine learning–based prediction of hospital admission among children in an emergency care center. Pediatric Emergency Care **39**(2), 80–86 (2023)
147. Ho, W., Ka Man Lee, C., To Sum Ho, G.: Optimization of the facility location-allocation problem in a customer-driven supply chain. Operations Management Research **1**, 69–79 (2008)
148. Hulshof, P.J.H., Kortbeek, N., Boucherie, R.J., Hans, E.W., Bakker, P.J.M.: Taxonomic classification of planning decisions in health care: a structured review of the state of the art in OR/MS. Health Systems **1**(2), 129–175 (2012)
149. Humagain, S., Sinha, R., Lai, E., Ranjitkar, P.: A systematic review of route optimisation and pre-emption methods for emergency vehicles. Transport reviews **40**(1), 35–53 (2020)
150. Hussain, M., Ajmal, M.M., Gunasekaran, A., Khan, M.: Exploration of social sustainability in healthcare supply chain. Journal of Cleaner Production **203**, 977–989 (2018)
151. Hutzschenreuter, A.K., Bosman, P.A., La Poutré, H.: Evolutionary multiobjective optimization for dynamic hospital resource management. In: International conference on evolutionary multi-criterion optimization, pp. 320–334. Springer (2009)
152. Ignatowicz, A., Tarrant, C., Mannion, R., El-Sawy, D., Conroy, S., Lasserson, D.: Organizational resilience in healthcare: a review and descriptive narrative synthesis of approaches to resilience measurement and assessment in empirical studies. BMC Health Services Research **23**(1), 376 (2023)
153. Iroju, O., Soriyan, A., Gambo, I., Olaleke, J., et al.: Interoperability in healthcare: benefits, challenges and resolutions. International Journal of Innovation and Applied Studies **3**(1), 262–270 (2013)
154. Ivanov, D.: Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transportation Research Part E: Logistics and Transportation Review **136**, 101,922 (2020)
155. Ivanov, D., Dolgui, A.: Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. a position paper motivated by covid-19 outbreak. International Journal of Production Research **58**(10), 2904–2915 (2020)
156. Ivanov, D., Dolgui, A.: A digital supply chain twin for managing the disruption risks and resilience in the era of industry 4.0. Production Planning & Control **32**(9), 775–788 (2021)

157. Ivezic, N., Jelisic, E., Jankovic, M., Kulvatunyou, B., Kehagias, D., Marjanovic, Z.: Advancing data exchange standards for interoperable enterprise networks. Proceedings http://ceur-ws.org ISSN **1613**, 0073 (2022)
158. Jadhav, J.S., Deshmukh, J.: A review study of the blockchain-based healthcare supply chain. Social Sciences & Humanities Open **6**(1), 100,328 (2022)
159. Jagtap, S.N., Potharaju, S., Amiripalli, S.S., Tirandasu, R.K., Jaidhan, B.: Interdisciplinary research for predictive maintenance of mri machines using machine learning. Journal of Current Science and Technology **15**(1), 78–78 (2025)
160. Jain, H., Deb, K.: An evolutionary many-objective optimization algorithm using reference-point based nondominated sorting approach, part ii: Handling constraints and extending to an adaptive approach. IEEE Transactions on Evolutionary Computation **18**(4), 602–622 (2013)
161. Jain, V., Mohan, U., Zacharia, Z., Sanders, N.R.: Improving patient satisfaction and outpatient diagnostic center efficiency using novel online real-time scheduling. Operations Research for Health Care **32**, 100,338 (2022)
162. Javadi Gargari, F., Sayad, M., Posht Mashhadi, S.A., Sadrnia, A., Nedjati, A., Yousefi Golafshani, T.: Five-echelon multiobjective health services supply chain modeling under disruption. Mathematical Problems in Engineering **2021**(1), 5587,392 (2021)
163. Jayaraman, R., Taha, K., Collazos, A.B.: Integrating supply chain data standards in healthcare operations and electronic health records. In: 2015 International Conference on Industrial Engineering and Operations Management (IEOM), pp. 1–9. IEEE (2015)
164. Jiménez-Delgado, G.I., Aslan, I., Hernández-Palma, H., Orozco Bohorquez, M., Acosta Ortega, F., Plazas-Alvarado, J., Jiménez-Coronado, A., Roncallo-Pichon, A., Morales-Espinosa, R.: Design of a framework based on mcdm and data analytics for improving the inventory management of supplies for clinical studies: A case study in a research center of a high complexity clinic. In: International Conference on Human-Computer Interaction, pp. 74–92. Springer (2025)
165. Jones, D., Tamiz, M.: Practical Goal Programming, vol. 141. Springer (2010)
166. Jones, D., Tamiz, M.: A Review of Goal Programming, pp. 903–926. Springer New York (2016)
167. Kalinaki, K., Shafik, W., Namuwaya, S., Namuwaya, S.: Perspectives, applications, challenges, and future trends of iot-based logistics. In: Navigating Cyber Threats and Cybersecurity in the Logistics Industry, pp. 148–171. IGI Global (2024)
168. Kaplan, R.S., Porter, M.E., et al.: How to solve the cost crisis in health care. Harvard Business Review **89**(9), 46–52 (2011)
169. Karatas, M., Yakıcı, E.: A multi-objective location analytics model for temporary emergency service center location decisions in disasters. Decision Analytics Journal **1**, 100,004 (2021)
170. Kasthuri, N., Meeradevi, T.: Ai-driven healthcare analysis. Smart Systems for Industrial Applications pp. 269–285 (2022)
171. Kaur, P., Pradhan, B.L., Priya, A.: TODIM approach for selection of inventory policy in supply chain. Mathematical Problems in Engineering **2022**(1), 5959,116 (2022)
172. Kaveh, M., Kaveh, M., Mesgari, M.S., Paland, R.S.: Multiple criteria decision-making for hospital location-allocation based on improved genetic algorithm. Applied Geomatics **12**, 291–306 (2020)
173. Kees, M.C., Bandoni, J.A., Moreno, M.S.: An optimization model for managing the drug logistics process in a public hospital supply chain integrating physical and economic flows. Industrial & Engineering Chemistry Research **58**(9), 3767–3781 (2019)
174. Khalifa, M., Albadawy, M., Iqbal, U.: Advancing clinical decision support: The role of artificial intelligence across six domains. Computer Methods and Programs in Biomedicine Update **5**, 100,142 (2024)

175. Khezr, S., Moniruzzaman, M., Yassine, A., Benlamri, R.: Blockchain technology in healthcare: A comprehensive review and directions for future research. Applied sciences **9**(9), 1736 (2019)
176. Khoshgehbari, F., Al-e, S.M.J.M., et al.: Ambulance location routing problem considering all sources of uncertainty: Progressive estimating algorithm. Computers & Operations Research **160**, 106,400 (2023)
177. Khoukhi, S., Bojji, C., Bensouda, Y.: A review of medical distribution logistics in pharmaceutical supply chain. International Journal of Logistics Systems and Management **34**(3), 297–326 (2019)
178. Knight, D.R., Aakre, C.A., Anstine, C.V., Munipalli, B., Biazar, P., Mitri, G., Valery, J.R., Brigham, T., Niazi, S.K., Perlman, A.I., et al.: Artificial intelligence for patient scheduling in the real-world health care setting: A metanarrative review. Health Policy and Technology **12**(4), 100,824 (2023)
179. Kou, G., Wu, W.: Multi-criteria decision analysis for emergency medical service assessment. Annals of Operations Research **223**, 239–254 (2014)
180. Kouwenberg, L.H., Cohen, E.S., Hehenkamp, W.J., Snijder, L.E., Kampman, J.M., Küçükkeles, B., Kourula, A., Meijers, M.H., Smit, E.S., Sperna Weiland, N.H., et al.: The carbon footprint of hospital services and care pathways: a state-of-the-science review. Environmental health perspectives **132**(12), 126,002 (2024)
181. Kryvonos, Y., Khorozov, O., Smolarz, A., Surtel, W., Kalizhanova, A.: Interoperability of the health care information resources. In: Recent Advances in Information Technology, pp. 83–103. CRC Press (2017)
182. Kumar, D., Kumar, D.: Modelling hospital inventory management using interpretive structural modelling approach. International Journal of Logistics Systems and Management **21**(3), 319–334 (2015)
183. Kumar, S., Dieveney, E., Dieveney, A.: Reverse logistic process control measures for the pharmaceutical industry supply chain. International Journal of Productivity and Performance Management **58**(2), 188–204 (2009)
184. Laganà, I.R., Colapinto, C.: Multiple criteria decision-making in healthcare and pharmaceutical supply chain management: a state-of-the-art review and implications for future research. Journal of Multi-Criteria Decision Analysis **29**(1-2), 122–134 (2022)
185. Lai, K.h., Cheng, T.E.: Just-in-time logistics. Routledge (2016)
186. Lane, H., Sarkies, M., Martin, J., Haines, T.: Equity in healthcare resource allocation decision making: a systematic review. Social science & medicine **175**, 11–27 (2017)
187. Lee, C.W., Kwak, N.: Strategic enterprise resource planning in a health-care system using a multicriteria decision-making model. Journal of Medical Systems **35**, 265–275 (2011)
188. Lee, D.J., Ding, J., Guzzo, T.J.: Improving operating room efficiency. Current Urology Reports **20**, 1–8 (2019)
189. Lee, I., Lee, K.: The internet of things (iot): Applications, investments, and challenges for enterprises. Business horizons **58**(4), 431–440 (2015)
190. van Lent, W.A., Sanders, E.M., van Harten, W.H.: Exploring improvements in patient logistics in dutch hospitals with a survey. BMC Health Services Research **12**, 1–9 (2012)
191. Liao, S.K., Chang, K.L.: Measure performance of hospitals using analytic network process (ANP). International Journal of Business Performance and Supply Chain Modelling **1**(2-3), 129–143 (2009)
192. Lima, J.d.S., França, J.M., de Menezes, J.S., Oliveira, A., Soares, M.S.: Layered Implementation View of a SOA Based Electronic Health Record. In: SEKE, pp. 323–328 (2016)
193. Love-Koh, J., Griffin, S., Kataika, E., Revill, P., Sibandze, S., Walker, S.: Methods to promote equity in health resource allocation in low-and middle-income countries: an overview. Globalization and health **16**, 1–12 (2020)

194. Lu, L., Wang, S.: Literature review of analytical models on emergency vehicle service: location, dispatching, routing and preemption control. In: 2019 IEEE intelligent transportation systems conference (ITSC), pp. 3031–3036. IEEE (2019)
195. Lyng, H.B., Macrae, C., Guise, V., Haraldseid-Driftland, C., Fagerdal, B., Schibevaag, L., Wiig, S.: Capacities for resilience in healthcare; a qualitative study across different healthcare contexts. BMC Health Services Research **22**(1), 474 (2022)
196. Majumder, R., Jana, S., Ghose, D.: Game theory-based decision making for the allocation of scarce medical resources in the covid-19 situation. IEEE Transactions on Systems, Man, and Cybernetics: Systems (2024)
197. Mannan, J.M., Myilvahanan, J.K., Yousuf, R.M., Selvan, K.S., Parameswaran, T.: Smart scheduling on cloud for traffic signal to emergency vehicle using iot. International Journal of Cloud Computing **10**(4), 356–369 (2021)
198. Marianov, V., ReVelle, C.: The queueing maximal availability location problem: a model for the siting of emergency vehicles. European Journal of Operational Research **93**(1), 110–120 (1996)
199. Marynissen, J., Demeulemeester, E.: Literature review on multi-appointment scheduling problems in hospitals. European Journal of Operational Research **272**(2), 407–419 (2019)
200. Masud, M., Gaba, G.S., Choudhary, K., Alroobaea, R., Hossain, M.S.: A robust and lightweight secure access scheme for cloud based e-healthcare services. Peer-to-peer Networking and Applications **14**(5), 3043–3057 (2021)
201. Mennella, C., Maniscalco, U., De Pietro, G., Esposito, M.: Ethical and regulatory challenges of AI technologies in healthcare: A narrative review. Heliyon **10**(4), e26,297 (2024)
202. Mercuri, R.T.: The hipaa-potamus in health care data security. Communications of the ACM **47**(7), 25–28 (2004)
203. Miran, L.D., Abduladheem, W., Abdullah, A.F., Al-Sharify, T.A., Ahmed, N.S., Ahmed, S.R., AlAqad, M., Algburi, S.: The role of artificial intelligence in enhancing english language communication and operational efficiency in logistics and transportation systems. In: 2024 8th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), pp. 1–8. IEEE (2024)
204. Misra, S., Pal, S., Pathak, N., Deb, P.K., Mukherjee, A., Roy, A.: i-AVR: IoT-Based Ambulatory Vitals Monitoring and Recommender System. IEEE Internet of Things Journal **10**(12), 10,318–10,325 (2023)
205. Mohamadi, N., Niaki, S.T.A., Taher, M., Shavandi, A.: An application of deep reinforcement learning and vendor-managed inventory in perishable supply chain management. Engineering Applications of Artificial Intelligence **127**, 107,403 (2024)
206. Moore, W., Frye, S.: Review of HIPAA, Part 1: History, Protected Health Information, and Privacy and Security Rules. Journal of Nuclear Medicine Technology **47**(4), 269–272 (2019)
207. Muller, M.: Essentials of inventory management. HarperCollins Leadership (2019)
208. Munavalli, J.R., Boersma, H.J., Rao, S.V., Van Merode, G.: Real-time capacity management and patient flow optimization in hospitals using ai methods. Artificial intelligence and Data mining in healthcare pp. 55–69 (2021)
209. Nagurney, A., Masoumi, A.H., Yu, M.: Supply chain network operations management of a blood banking system with cost and risk minimization. Computational management science **9**, 205–231 (2012)
210. Namakshenas, M., Mazdeh, M.M., Braaksma, A., Heydari, M.: Appointment scheduling for medical diagnostic centers considering time-sensitive pharmaceuticals: A dynamic robust optimization approach. European journal of operational research **305**(3), 1018–1031 (2023)
211. Narayanaswamy, K., Hajarnavis, H.R.: Maximizing operational efficiency in healthcare: The impact of private equity. Journal of Healthcare Management Standards (JHMS) **2**(1), 1–9 (2022)

212. Naresh, V.S., Pericherla, S.S., Murty, P.S.R., Reddi, S.: Internet of things in healthcare: Architecture, applications, challenges, and solutions. Computer Systems Science & Engineering **35**(6) (2020)
213. Nargundkar, A., Kulkarni, A.J.: A comprehensive review of goal programming problems and constraint handling approaches. Handbook of Formal Optimization pp. 1–32 (2023)
214. Năstase, P., Năstase, F., Ionescu, C.: Challenges Generated By the Implementation of the IT Standards COBIT 4.1, ITIL V3 and ISO/IEC 27002 in Enterprises. Economic Computation & Economic Cybernetics Studies & Research **43**(3) (2009)
215. Negri, M., Cagno, E., Colicchia, C., Sarkis, J.: Integrating sustainability and resilience in the supply chain: A systematic literature review and a research agenda. Business Strategy and the Environment **30**(7), 2858–2886 (2021)
216. O'Connell, M., Barry, J., Hartigan, I., Cornally, N., Saab, M.M.: The impact of electronic and self-rostering systems on healthcare organisations and healthcare workers: A mixed-method systematic review. Journal of Clinical Nursing **33**(7), 2374–2387 (2024)
217. Ozcan, Y.A.: Quantitative methods in health care management: techniques and applications. John Wiley & Sons (2005)
218. Papathanasiou, J., Ploskas, N.: TOPSIS, pp. 1–30. Springer International Publishing (2018)
219. Patel, P., Samantaray, H., Mansharamani, R., Vora, D., Goyal, A., Gupta, A.: Analysis of decentralized pharmaceutical supply chain: A systematic review. In: 2023 International Conference on Artificial Intelligence and Smart Communication (AISC), pp. 800–805. IEEE (2023)
220. Patrick, J., Puterman, M.L., Queyranne, M.: Dynamic multipriority patient scheduling for a diagnostic resource. Operations research **56**(6), 1507–1525 (2008)
221. Paucar, E.W.C., Paucar, H.Z.C., Paucar, D.R.C., Paucar, G.V.C., Sotelo, C.G.M.: Artificial Intelligence as an Innovation Tool in Hospital Management: a Study Based on the SDGs. Journal of Lifestyle and SDGs Review **5**(1), e04,089–e04,089 (2025)
222. de Paula Vidal, G.H., Caiado, R.G.G., Scavarda, L.F., Ivson, P., Garza-Reyes, J.A.: Decision support framework for inventory management combining fuzzy multicriteria methods, genetic algorithm, and artificial neural network. Computers & Industrial Engineering **174**, 108,777 (2022)
223. Penn, M.L., Potts, C.N., Harper, P.R.: Multiple criteria mixed-integer programming for incorporating multiple factors into the development of master operating theatre timetables. European Journal of Operational Research **262**(1), 194–206 (2017)
224. Perals, P.O., Rambaud, S.C., García, J.S.: Quality of care and patient satisfaction: Future trends and economic implications for the healthcare system. Journal of Economic Surveys (2024)
225. Pérez Vergara, I.G., Arias Sánchez, J.A., Poveda-Bautista, R., Diego-Mas, J.A.: Improving Distributed Decision Making in Inventory Management: A Combined ABC-AHP Approach Supported by Teamwork. Complexity **2020**(1), 6758,108 (2020)
226. Prabhod, K.J.: The role of artificial intelligence in reducing healthcare costs and improving operational efficiency. Quarterly Journal of Emerging Technologies and Innovations **9**(2), 47–59 (2024)
227. Prabu, M., Diviya, M., Bhuvaneswari, R., Reddy, D.S., Venkatesan, K., Natarajan, A.K.: The impact and integration of cloud computing for enhanced patient care and operational efficiency. In: Technologies for Sustainable Healthcare Development, pp. 277–299. IGI Global (2024)
228. Pradhan, N.A., Samnani, A.A.B.A., Abbas, K., Rizvi, N.: Resilience of primary healthcare system across low-and middle-income countries during covid-19 pandemic: a scoping review. Health Research Policy and Systems **21**(1), 98 (2023)

229. Prajwal, V., Rahul, I., Chayadevi, M., et al.: Increasing emergency response time: A smart gps and iot-based approach for ambulance optimization. In: 2024 Second International Conference on Advances in Information Technology (ICAIT), vol. 1, pp. 1–5. IEEE (2024)
230. Qadri, Y.A., Nauman, A., Zikria, Y.B., Vasilakos, A.V., Kim, S.W.: The future of healthcare internet of things: a survey of emerging technologies. IEEE Communications Surveys & Tutorials **22**(2), 1121–1167 (2020)
231. Qu, Q., Ma, Z., Clausen, A., Jørgensen, B.N.: A comprehensive review of machine learning in multi-objective optimization. In: 2021 IEEE 4th International Conference on Big Data and Artificial Intelligence (BDAI), pp. 7–14. IEEE (2021)
232. Quiel, Y.C., Saavedra, A., Villarreal, V.: Coding and interoperability standards in eSalud: projection evaluation AmIHEALTH. Revista Cubana de Información en Ciencias de la Salud (ACIMED) **30**(3), 1–23 (2019)
233. Rachmania, I.N., Basri, M.H.: Pharmaceutical inventory management issues in hospital supply chains. Management **3**(1), 1–5 (2013)
234. Raghupathi, W., Kesh, S.: Interoperable electronic health records design: towards a service-oriented architecture. E-service Journal **5**(3), 39–57 (2007)
235. Rahimi, I., Gandomi, A.H.: A comprehensive review and analysis of operating room and surgery scheduling. Archives of Computational Methods in Engineering **28**(3), 1667–1688 (2021)
236. Rahman, S.u., Smith, D.K.: Use of location-allocation models in health service development planning in developing nations (2000)
237. Rais, A., Viana, A.: Operations research in healthcare: a survey. International transactions in operational research **18**(1), 1–31 (2011)
238. Rajagopalan, H.K., Saydam, C., Xiao, J.: A multiperiod set covering location model for dynamic redeployment of ambulances. Computers & Operations Research **35**(3), 814–826 (2008)
239. Rathore, Y., Sinha, U., Haladkar, J.P., Mate, N.R., Bhosale, S.A., Chobe, S.V.: Optimizing Patient Flow and Resource Allocation in Hospitals using AI. In: 2023 International Conference on Artificial Intelligence for Innovations in Healthcare Industries (ICAIIHI), vol. 1, pp. 1–6. IEEE (2023)
240. Rauf, M., Guan, Z., Sarfraz, S., Mumtaz, J., Almaiman, S., Shehab, E., Jahanzaib, M.: Multi-criteria inventory classification based on multi-criteria decision-making (MCDM) technique. In: Advances in Manufacturing Technology XXXII, pp. 343–348. IOS Press (2018)
241. Reda, M., Kanga, D.B., Fatima, T., Azouazi, M.: Blockchain in health supply chain management: State of art challenges and opportunities. Procedia Computer Science **175**, 706–709 (2020)
242. Reis, L.F., Ferreira, D.G., Maranhao, P.A., Cruz-Correia, R., Vieira-Marques, P.: Integration through mapping—An OpenEHR based approach for research oriented integration of health information systems. In: 2018 13th Iberian conference on information systems and technologies (CISTI), pp. 1–5. IEEE (2018)
243. Rejeb, A., Rejeb, K., Simske, S.J., Treiblmaier, H.: Drones for supply chain management and logistics: a review and research agenda. International Journal of Logistics Research and Applications **26**(6), 708–731 (2023)
244. Romero, C.: Handbook of critical issues in goal programming. Elsevier (2014)
245. Rong, G., Mendez, A., Assi, E.B., Zhao, B., Sawan, M.: Artificial intelligence in healthcare: review and prediction case studies. Engineering **6**(3), 291–301 (2020)
246. Russell, R.S., Taylor, B.W.: Operations and supply chain management. John Wiley & Sons (2019)
247. Saaty, R.W.: The analytic hierarchy process—what it is and how it is used. Mathematical Modelling **9**(3-5), 161–176 (1987)

248. Saaty, T.L.: Decision making—the analytic hierarchy and network processes (AHP/ANP). Journal of Systems Science and Systems Engineering **13**, 1–35 (2004)
249. Saaty, T.L.: Decision making with the analytic hierarchy process. International Journal of Services Sciences **1**(1), 83–98 (2008)
250. Saghafian, S., Austin, G., Traub, S.J.: Operations research/management contributions to emergency department patient flow optimization: Review and research prospects. IIE Transactions on Healthcare Systems Engineering **5**(2), 101–123 (2015)
251. Saha, E., Ray, P.K.: Modelling and analysis of inventory management systems in healthcare: A review and reflections. Computers & Industrial Engineering **137**, 106,051 (2019)
252. Şahin, T., Ocak, S., Top, M.: Analytic hierarchy process for hospital site selection. Health Policy and Technology **8**(1), 42–50 (2019)
253. Sarangi, S., Ghosh, D.: The impact of industry 4.0 technologies enable supply chain performance and quality management practice in the healthcare sector. The TQM Journal (2024)
254. Sawik, B.: Lexicographic approach to health care optimization. In: Applications of Management Science, pp. 181–201. Emerald Group Publishing Limited (2015)
255. Sawik, B.: Weighted-sum approach to health care optimization. In: Applications of Management Science, pp. 163–180. Emerald Group Publishing Limited (2015)
256. Sbai, N., Benabbou, L., Berrado, A.: Comparison of MCDM Methods for Multi-echelon Inventory System Selection Problem. In: Proceedings of the 13th International Conference on Intelligent Systems: Theories and Applications, pp. 1–7 (2020)
257. Sbai, N., Benabbou, L., Berrado, A.: Multi-echelon inventory system selection: Case of distribution systems. International Journal of Supply & Operations Management **9**(1) (2022)
258. Scherrer, C.R.: The allocation of scarce resources in public health. Georgia Institute of Technology (2005)
259. Schniederjans, M.: Goal programming: Methodology and applications: Methodology and applications. Springer Science & Business Media (1995)
260. Schwartz, R.L.: Resource allocation and vulnerable groups. In: Rights and Resources, pp. 543–565. Routledge (2024)
261. Schweitzer, M., Steger, B., Hoerbst, A., Augustin, M., Pfeifer, B., Hausmann, U., Baumgarten, D.: Data exchange standards in teleophthalmology: Current and future developments. dHealth 2022 pp. 270–277 (2022)
262. Senna, P., Reis, A., Dias, A., Coelho, O., Guimarães, J., Eliana, S.: Healthcare supply chain resilience framework: antecedents, mediators, consequents. Production Planning & Control **34**(3), 295–309 (2023)
263. Shafik, W.: Machine learning techniques for multicriteria decision-making. In: Multi-Criteria Decision-Making and Optimum Design with Machine Learning, pp. 165–194. CRC Press (2025)
264. Shamayleh, A., Awad, M., Farhat, J.: IoT based predictive maintenance management of medical equipment. Journal of Medical Systems **44**(4), 72 (2020)
265. Shehadeh, K.S., Snyder, L.V.: Equity in stochastic healthcare facility location. In: Uncertainty in Facility Location Problems, pp. 303–334. Springer (2023)
266. Shen, J., Liu, K., Ma, C., Zhao, Y., Shi, C.: Bibliometric analysis and system review of vehicle routing optimization for emergency material distribution. Journal of traffic and transportation engineering (English edition) **9**(6), 893–911 (2022)
267. Shu, S., Qi, H., Yang, Y., Qiwen, X., Xinguo, Q.: Exchanging Chinese Medical Information Based on HL7 FHIR. Data Analysis and Knowledge Discovery **5**(11), 13–28 (2021)
268. Silva, B.V., Holm-Nielsen, J.B., Sadrizadeh, S., Teles, M.P., Kiani-Moghaddam, M., Arabkoohsar, A.: Sustainable, green, or smart? pathways for energy-efficient healthcare buildings. Sustainable Cities and Society **100**, 105,013 (2024)

269. Silva Gallino, J.P., de Miguel, M., Briones, J.F., Alonso, A.: Domain-specific multi-modeling of security concerns in service-oriented architectures. In: International Workshop on Web Services and Formal Methods, pp. 128–142. Springer (2011)
270. Sivasangari, A., Lakshmanan, L., Ajitha, P., Deepa, D., Jabez, J.: Big data analytics for 5G-enabled IoT healthcare. Blockchain for 5G-Enabled IoT: The new wave for Industrial Automation pp. 261–275 (2021)
271. Starfield, B.: Primary care: balancing health needs, services, and technology. Oxford University Press (1998)
272. Sun, K., Gu, Y., Wan Fei Ma, K., Zheng, C., Wu, F.: Medical supplies delivery route optimization under public health emergencies incorporating metro-based logistics system. Transportation Research Record **2678**(7), 111–131 (2024)
273. Teixeira, J.C.V.: Public facility planning models with single and multiple services: Models, solution methods and applications. Ph.D. thesis, Universidade de Coimbra (Portugal) (2012)
274. Thakkar, J.J.: Multi-criteria decision making, vol. 336. Springer (2021)
275. Tian, F.: An agri-food supply chain traceability system for china based on rfid & blockchain technology. In: 2016 13th international conference on service systems and service management (ICSSSM), pp. 1–6. IEEE (2016)
276. Tluli, R., Badawy, A., Salem, S., Barhamgi, M., Mohamed, A.: A survey of machine learning innovations in ambulance services: Allocation, routing, and demand estimation. IEEE Open Journal of Intelligent Transportation Systems (2024)
277. Topol, E.: Deep medicine: how artificial intelligence can make healthcare human again. Hachette UK (2019)
278. Torab-Miandoab, A., Samad-Soltani, T., Jodati, A., Akbarzadeh, F., Rezaei-Hachesu, P.: A unified component-based data-driven framework to support interoperability in the healthcare systems. Heliyon **10**(15) (2024)
279. Toub, M., Souissi, O., Achchab, S.: Operating room scheduling 2019 survey. International Journal of Medical Engineering and Informatics **14**(1), 1–30 (2022)
280. Vaidya, O.S., Kumar, S.: Analytic hierarchy process: An overview of applications. European Journal of Operational Research **169**(1), 1–29 (2006)
281. Van Houdenhoven, M., Hans, E.W., Klein, J., Wullink, G., Kazemier, G.: A norm utilisation for scarce hospital resources: evidence from operating rooms in a dutch university hospital. Journal of Medical Systems **31**, 231–236 (2007)
282. Veenstra, M., Roodbergen, K.J., Coelho, L.C., Zhu, S.X.: A simultaneous facility location and vehicle routing problem arising in health care logistics in the netherlands. European Journal of Operational Research **268**(2), 703–715 (2018)
283. Volkov, I., Radchenko, G., Tchernykh, A.: Digital twins, internet of things and mobile medicine: a review of current platforms to support smart healthcare. Programming and Computer Software **47**, 578–590 (2021)
284. Vollmer, M.A., Glampson, B., Mellan, T., Mishra, S., Mercuri, L., Costello, C., Klaber, R., Cooke, G., Flaxman, S., Bhatt, S.: A unified machine learning approach to time series forecasting applied to demand at emergency departments. BMC Emergency Medicine **21**, 1–14 (2021)
285. Wan, J., AAH Al-awlaqi, M., Li, M., O'Grady, M., Gu, X., Wang, J., Cao, N.: Wearable iot enabled real-time health monitoring system. EURASIP Journal on Wireless Communications and Networking **2018**(1), 1–10 (2018)
286. Weatherly, H., Drummond, M., Claxton, K., Cookson, R., Ferguson, B., Godfrey, C., Rice, N., Sculpher, M., Sowden, A.: Methods for assessing the cost-effectiveness of public health interventions: key challenges and recommendations. Health policy **93**(2-3), 85–92 (2009)
287. Wiig, S., Aase, K., Billett, S., Canfield, C., Røise, O., Njå, O., Guise, V., Haraldseid-Driftland, C., Ree, E., Anderson, J.E., et al.: Defining the boundaries and operational concepts of

resilience in the resilience in healthcare research program. BMC Health Services Research **20**, 1–9 (2020)
288. Wild, T.: Best practice in inventory management. Routledge (2017)
289. Wright, A., Sittig, D.F., Ash, J.S., Sharma, S., Pang, J.E., Middleton, B.: Clinical decision support capabilities of commercially-available clinical information systems. Journal of the American Medical Informatics Association **16**(5), 637–644 (2009)
290. Xing, X., Wu, H., Wang, L., Stenson, I., Yong, M., Del Ser, J., Walsh, S., Yang, G.: Non-imaging medical data synthesis for trustworthy ai: A comprehensive survey. ACM Computing Surveys **56**(7), 1–35 (2024)
291. Yang, C.H., Hsu, W., Wu, Y.L.: A hybrid multiple-criteria decision portfolio with the resource constraints model of a smart healthcare management system for public medical centers. Socio-economic planning sciences **80**, 101,073 (2022)
292. Ye, H., Kim, H.: Locating healthcare facilities using a network-based covering location problem. GeoJournal **81**, 875–890 (2016)
293. Ye, Y., Huang, L., Wang, J., Chuang, Y.C., Pan, L.: Patient allocation method in major epidemics under the situation of hierarchical diagnosis and treatment. BMC Medical Informatics and Decision Making **22**(1), 331 (2022)
294. Zheng, F., Du, L., Li, X., Zhang, J., Tian, B., Jallad, R.: Multi-objective medical supplies distribution open vehicle routing problem with fairness and timeliness under major public health emergencies. Management System Engineering **2**(1), 5 (2023)
295. Zhong, L., Lopez, D., Pei, S., Gao, J.: Healthcare system resilience and adaptability to pandemic disruptions in the united states. Nature Medicine **30**(8), 2311–2319 (2024)
296. Zonderland, M.E., Leeftink, A.G., Braaksma, A., Boucherie, R.J., Hans, E.W., Kortbeek, N.: Making an impact on healthcare logistics. Handbook of healthcare logistics: bridging the gap between theory and practice pp. 1–13 (2021)