A Review of the Healthcare-Management (Modeling) Literature Published in *M&SOM*

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Healthcare systems throughout the world are under pressure to widen access, improve efficiency and quality of care, and reduce inequity. Achieving these conflicting goals requires innovative approaches, utilizing new technologies, data analytics, and process improvements. The operations management community has taken on this challenge: more than 10% of articles published in *M&SOM* in the period from 2009 to 2018 has developed analytical models that aim to inform healthcare operational decisions and improve medical decision-making. This article presents a review of the research published in *M&SOM* on healthcare management since its inception 20 years ago and reflects on opportunities for further research.

Key words: Healthcare; modeling; review; *M&SOM*

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1. Introduction

"Ensuring healthy lives and promoting the well-being at all ages is essential to sustainable development."[1] Hence, countries worldwide strive towards more efficient and effective mechanisms to prevent disease, prolong life, and promote health in populations, as well as treating disease. While advances in medicine and medical and information technologies often take the spotlight in this quest, public and population health also play a significant role, with a focus on prevention and promotion of healthy behaviors (e.g., through education or policy). In recent years, significant progress has been made towards the goal of improving health and well-being around the world, in part thanks to the United Nations Millennium Development Goals and related efforts. For example, between 1990 and 2015 the global under-five mortality rate dropped from 90 to 43 deaths per 1,000 live births, the maternal mortality ratio has declined by 45%, and malaria incidence rate has fallen by an estimated 37% (United Nations 2015).

However, there are still many challenges, with some commonalities but also differences across different regions and populations. Some countries in the developed world have seen a tremendous increase in healthcare spending, while the health outcomes did not improve at a similar rate. For example, in 2017 the United States (US) spent 17% of its gross domestic product on healthcare;

the equivalent figure for the largest European countries was 9–12% (Sawyer and Cox 2018). Despite the increase in spending, several key health outcome measures such as life expectancy and the prevalence of chronic conditions continue to be worse in the US compared to other developed countries (Squires and Anderson 2015). This may be explained in part by the relatively small investment of the US economy into social services, such as housing assistance, employment programs, disability benefits, and food security, which are among the determinants of health. On the bright side, there is a renewed emphasis towards improving quality of care and patient outcomes, with a value-based versus activity-based focus (Porter 2009) and a trend towards informed and shared decision-making (Barry and Edgman-Levitan 2012).

Access to healthcare and equity remain important challenges worldwide, and hence, the United Nations Sustainable Development Goals focus on "leaving no one behind" (Fullman et al. 2017). While access in developing countries may focus on basic coverage such as vaccinations and maternal health, in developed countries it also expands to include timely access, e.g., the ability to make an appointment with a specialist in a timely manner, short wait times in emergency departments, geographic proximity to primary care providers, specialists, or pharmacists, or easy access to life-saving procedures and pharmaceutical products.

To continue on the path of improving population health, we must strive to widen **access** (e.g., by improving availability of vaccines and reducing waiting times), improve **efficiency** and **quality** of care (e.g., by increasing quality-adjusted life years while minimizing costs), and promote **equity** (e.g., ensure that access and outcomes are comparable across different geographical areas, demographic groups, income levels, etc.) (Ayer et al. 2014). Achieving these improvements is, to a large extent, an operational challenge; these improvements can only be achieved by identifying more efficient ways of organizing and delivering care (Green 2012).

The Operations Management (OM) community has responded to this opportunity by adapting the analytical toolkits developed by our field to the challenges and decisions faced by various players in health systems, including policymakers, healthcare delivery organisations, and medical professionals. The goal of this review is to celebrate the knowledge generated by *M&SOM* since its inception 20 years ago in this area, and to briefly reflect on opportunities for future research. The focus is exclusively on modeling work; a companion review (KC et al. 2020) provides an overview of the empirical work.[i]

Research included in this review was published in *M&SOM*, between 1999 and April 2019, and featured one or more of the following words in the title, abstract, or body: health, health-care,

[i] We also note the recent review paper Dai and Tayur (2018) that examines recent trends in healthcare operations and provides a review of the research published in *Management Science*, *M&SOM*, and *Operations Research* in the period 2013–17.

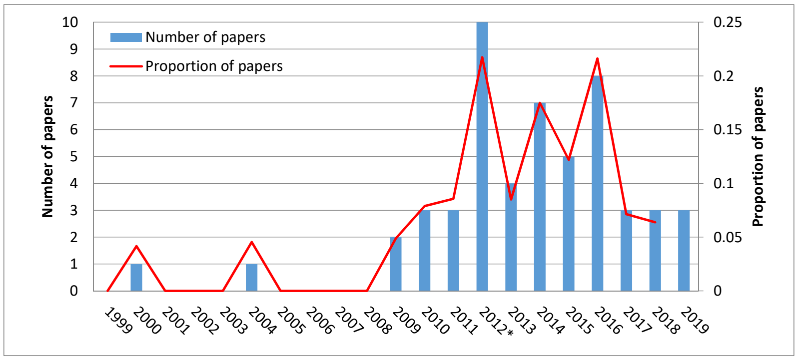

Figure 1 **Number of papers (left vertical axis) and proportion of papers (right vertical axis) published in M&SOM in healthcare management (modeling) during 1999 and April 2019, including a special issue in 2012.**

healthcare, patient, physician, diagnosis, pharmaceutical, drug, hospital. From this list we have excluded any publication that was not related to healthcare management, it was not a complete paper (e.g., errata, extended abstracts), its main methodological toolkit was not modeling, and any paper that identified healthcare management as one potential area of application but the work's main contribution was to a different area (e.g., call centers) or was primarily methodological (e.g., estimating waiting times in novel queueing systems). This procedure identified 53 papers. Figure 2 shows a world cloud of the keywords.

A time series of the number of healthcare modeling papers published in *M&SOM* (Figure 1) shows the growth in this area: only 2 healthcare modeling papers were published in the first 10 years (1999–2008), followed by 48 papers in the next 10 years (2009–2018), with another three published in the first issue of 2019. During 2009–2018, 11.6% of papers published in *M&SOM* were on healthcare modeling (4.8 papers per year, on average), including a special issue on Healthcare Management in 2012 with 8 papers (Golden and Seidmann 2012).

The review is organized in seven thematic sections. Work pertaining to Clinic, Hospital, Blood Bank, Ambulance Service, and Pharmaceutical Industry operations is discussed in Sections 2–6. Section 7 presents work that spans the boundaries of a single organization or sector and Section 8 discusses work on Medical Decision-Making. We conclude with a discussion of opportunities for future research.

2. Clinic Operations Management

Clinics are healthcare facilities that provide ambulatory care for patients who do not require admission to hospital. They may be affiliated to hospital systems or may be independent and typically cover a wide array of patient needs, from primary care to highly specialized diagnostics and treatments. While decisions in clinic operations management span a large range, papers published in *M&SOM* primarily focus on patient appointment and staff scheduling.

Figure 2 **Cloud of keywords of healthcare management (modeling) papers published in M&SOM.**

The journey of a patient visiting a clinic starts with booking an appointment. Appointment scheduling decisions in this setting consider the availability of providers, uncertainty about the patient condition and care needs, possibility of patient delays in arrival or 'no shows', possibility of walk-ins or patients with urgent needs who need to be seen without an appointment, etc. Eight papers published in *M&SOM* look at different aspects of this problem.

In a 'traditional' clinic setting, appointments are scheduled in advance of the appointment day. However, it is common that some patients do not show up to their appointment, while other patients with urgent needs may arrive at the clinic without an appointment and request services. Luo et al. (2012) study scheduling decisions considering patient 'no shows' as well as urgent arrivals. Zacharias and Pinedo (2017) examine a multiple server system and make scheduling and overbooking recommendations to offset the cost associated with patient no shows. Mak et al. (2014) observe that sequencing appointments with random service durations has some similarities to the problem of inventory management with random demand. They develop approximations that can be used to sequence appointments to reduce patient waiting time and provider idle time. While most papers in the literature assume that patients will accept any appointment time slot offered to them, Wang and Gupta (2011) consider patient preferences over different appointment slots, and also incorporate the clinic's learning of patient preferences over time into scheduling decisions.

Robinson and Chen (2010) focus on the relatively new 'open access'[2] scheduling practice, where same-day patients call in early in the morning for appointments later that day. The authors find that in most cases, the open-access schedule significantly outperforms the traditional schedule in terms of the weighted sum of patients' waiting time, doctor's idle time, and doctor's overtime. In a similar setting, Liu et al. (2010) consider both patient no shows and appointment cancellations, and develop heuristics for dynamically scheduling patients to different days. Their work largely confirms the benefits of open access but only when patient load is low.

Most of the work on appointment scheduling assumes that the costs of physician idle time and patient waiting time are known. Robinson and Chen (2011) present a simple and elegant method for estimating the relative magnitude of these costs, which is a critical input for scheduling decisions. The method combines observational data on physician utilization and simple queueing theory.

In addition to offering appointments in a timely fashion, clinics aim to provide high-quality of care. Among others, two factors play a key role: the customer service, as perceived by the patient; and whether the providers are in possession of the right information to treat the patients. The following papers examine these two factors.

Soteriou and Chase (2000) recognize that patient-perceived quality of service depends on a number of operational variables (e.g., staff responsiveness, reliability, time staff spend with patients). They solicit patient preferences using survey methods, and develop a robust optimization approach to provide guidelines on how to maximize patient-perceived quality while controlling costs. The robust optimization framework allows the authors to provide operational guidelines that perform well despite uncertainty in the model's input parameters.

Baron et al. (2016) study a diagnostic clinic where patients visit multiple independent stations. The clinic aims to minimize patient overall time in the clinic and time spent waiting at individual stations. To manage the second objective, the authors show empirically that individual servers deploy strategic idleness – when a queue builds up at a downstream server the upstream server temporarily idles (or reduces service rate) to allow for the downstream queue to dissipate. The authors develop dynamic scheduling policies that combine threshold-based strategic idleness and show (via simulation) that these policies can help manage both objectives simultaneously.

Lahiri and Seidmann (2012) combine an empirical investigation with a queuing model to study information flows in the context of a radiology clinic. They find that failure to gather the necessary clinical information in earlier steps of the patient journey can cause significant delays in later steps - a phenomenon the authors coin as information 'hang-over.' When a new information system was implemented, instances of information hang-overs were reduced at the expense of increasing the service time at the bottleneck server, the radiologist, who now had to navigate through a more complex screen sequence. The authors develop a novel queuing model that explicitly captures information hang-overs and explains why reducing hang-overs has cut the observed report turnaround times for diagnostic mammographies by 50% despite the associated increase in the radiologist's utilization.

3. Hospital Operations Management

Hospitals are major healthcare facilities with multiple care units, such as an emergency department (ED), intensive care units, operating rooms, inpatient wards, etc. and also support units such as pharmacy and radiology. One third of healthcare expenditures in the US occur in hospitals (Martin et al. 2018) and there are numerous opportunities for operational improvements, for example in capacity planning and management (Green 2005). The research published in *M&SOM* on hospital operations focuses on managing the operations of various hospital units and services, such as EDs and inpatient wards.

3.1. Managing Emergency Departments

Emergency Departments offer care to patients who present without prior appointment. In the US, in 2015 there were 136.9 million visits to EDs, corresponding to 43.3 visits per 100 people. Similar to clinics, EDs also strive to balance provider/resource utilization with timely and high quality care.[3] Nevertheless, nearly half of EDs operate at or above capacity, leading to long patient waiting times, which vary by location and facility. In the US, from 2003 through 2009, the mean wait time increased from 46.5 minutes to 58.1 minutes (Hing and Bhuiya 2012). Ang et al. (2015) combine queueing theory with statistical learning models to develop real-time estimates for ED waiting times. The authors show that their approach generates more accurate predictions than methods currently used in practice.

3.1.1. Triage Decisions Triage refers to the prioritization of patients in the ED based on the assessment of the severity of patients' conditions, such that the most critically ill or injured patients are seen first. Argon and Ziya (2009) examine the impact of accounting for the uncertainty in patients' true needs on the prioritization protocols. Saghafian et al. (2014) show that designing prioritization protocols that use information about patient complexity as well as patient needs can further improve operational performance and patient safety. Chan et al. (2013) design a new system for prioritizing burn-injured patients following a catastrophic event. Such patients need to be transferred to dedicated burn beds within three to five days. Using historical data from previous burn catastrophes, they show that their proposed scheme outperforms other triage methods, but nevertheless it is unlikely to be able to allow New York City to be able to meet the federal target of admitting 400 burn patients.

In addition to 'normal' day-to-day demand, EDs experience surge demand during natural or man-made disasters or mass casualty events. Mills et al. (2013) make recommendations on how to augment triage decisions while responding to a mass casualty event considering the limited resources and the time-dependent nature of the patients' survival probability.

3.1.2. Emergency Department Resource Planning and Management When the patient levels in an ED reach to a level such that offering quality care for additional patients is no longer possible, the ED may go on (full or partial) 'diversion,' i.e., ambulances are redirected to another facility until the crowding in the ED subsides. Xu and Chan (2016) show that EDs can dynamically manage congestion by using information about predicted future patient arrivals and exercising admission control proactively, for example, redirecting patients before the ED gets too busy, as opposed to reactively after congestion builds up.

Yom-Tov and Mandelbaum (2014) suggest a novel queueing model that captures some of the nuances of providing ED care. In particular, in their model, patients may return to the system to receive service several times. They develop time-varying fluid and diffusion approximations to come up with staffing policies that are shown to perform well. Dobson et al. (2012) examine the interaction between junior (resident) physicians who may batch patients before seeking the input of a senior (attending) physician in the context of the ED at a teaching hospital. More specifically, the authors develop a (tandem) queueing model to examine the impact of batching on throughput. They find that the throughput-optimal batching policy is dynamic and for static policies, while throughput is increasing in the number of patients batched, this comes at the expense of patient flow time.

3.2. Hospital Inpatient Wards

Hospitals consist of wards (departments), which are sometimes referred to as inpatient wards if they have beds. Examples include neurology, cardiology, and oncology. Patients can be admitted to wards after an ED visit, after surgery, or via direct admit. For example, in the US, around 9% of ED visits resulted in hospital admission.[4]

Best et al. (2015) examine whether hospitals should pool resources by building large general-purpose wings to achieve economies of scale, or small specialized wings that benefit from economies of focus and protect beds for patients that generate higher 'utility' for the hospital. Utility in this context can be a measure of financial or societal benefit. The authors develop an optimization model and generate useful guidelines for quantifying the benefits and costs associated with focused wings; for example, focused wings may decrease overall bed occupancy and limit access for some types of patients, but nevertheless increase patient throughput.

Huh et al. (2013) examine the trade-off between reserving sufficient resources for treating emergency patients immediately, while also treating electives (that can wait) in a timely fashion. The authors present a general framework, where there are multiple resources (e.g., staff, equipment) in a stochastic and non-stationary environment. Since the optimal policy is difficult to compute, the authors provide structural properties and computationally efficient approximations for the optimal capacity to be reserved for emergency jobs. In a numerical study, the best approximation performs within 1.8% of the optimal policy.

3.3. Operating Room Scheduling

Operating rooms are major cost and revenue centers for most hospitals, performing scheduled and emergency procedures. Since operating-room resources (space, equipment, personnel) are expensive, there has been considerable attention on surgery scheduling and staff planning to improve operating room utilization; see Zhu et al. (2018) for a recent review.

Among the papers publishes in *M&SOM*, Day et al. (2012), Ozen et al. (2015), and Freeman et al. (2015) use optimization techniques for surgery scheduling to improve operating room utilization. The first paper examines the frequently used practice of reserving an operating room for a 'block' of time to grant exclusive access to a specific surgeon irrespective of their actual surgery schedule. The results show that using 'shared' as opposed to exclusive block time, where capacity constraints are only met in expectation, can offer large benefits. Ozen et al. (2015) develop a data-driven optimization approach to improve scheduling practices for spine surgeries. The authors report that a pilot implementation with Mayo Clinic significantly increased utilization and reduced overtime. Freeman et al. (2015) use a scenario-based optimization approach considering the uncertainty in surgery durations and demand for urgent surgeries. The authors develop heuristics to solve the surgery scheduling problem in a reasonable time for practical-sized instances, and demonstrate the improvements that scenario-based optimization offers over deterministic models.

3.4. Staffing

Nurse staffing is the largest hospital expense. Therefore, models that inform staffing decisions are of particular interest to healthcare systems. Wang and Gupta (2014) focus on providing near-optimal heuristic staffing guidelines in the presence of empirically documented high and heterogeneous nurse absenteeism. He et al. (2012) study operating room nurse staffing under substantial uncertainty regarding daily workload. Using a 'newsvendor' framework, the authors examine how the optimal staffing cost changes as the available information increases. Using a real dataset, they find that hospitals could reduce their staffing cost by more than 39% if they could defer staffing decisions until they have information about the type of surgeries that are going to be performed.

4. Blood Collection and Inventory Management

Blood products (including red blood cells, plasma, and platelets) are perishable and essential for patient care in hospitals; hence, blood collection and inventory management strives to have sufficient inventory to meet patient needs while minimizing waste due to expiry (Stanger et al. 2012).

Three papers published in *M&SOM* examine the operational decisions associated with the collection and management of blood inventory. Ayer et al. (2019) worked with the American Red Cross to develop a mathematical program to improve the location and the timing decisions of blood collection that is to be processed into cryoprecipitate, a blood product used for controlling massive hemorrhaging. The authors devised a novel collection method that has been implemented by the American Red Cross in one manufacturing facility, resulting in more reliable supply and an impressive 40% reduction in collection cost. Sarhangian et al. (2017) study practical threshold-based blood-inventory management policies that aim to reduce the age of red blood cells that are being transfused without compromising availability. Such age reduction was shown to be associated with better clinical outcomes. The authors illustrate their findings using a simulation study calibrated to data from a Canadian hospital. Zhou et al. (2011) study the inventory of platelets, a perishable blood component with a three-day life span. The authors study a periodic review model under two replenishment modes, where in addition to regular orders, the manager can place an additional expedited order characterized by an order-up-to level policy. The authors show that there exists a policy that minimizes costs, and develop an algorithm for determining this policy. They illustrate the performance of the policy using a numerical illustration and study its sensitivity to model parameters.

5. Ambulance Service Operations

Emergency medical service systems (EMS) are responsible for dispatching ambulances to patients in need of acute care. According to a survey of 1,300 EDs in the US, in 2013 17% of patients arrived to EDs by ambulance.[5] There are several decisions related to ambulance services, such as ambulance station locations and dispatch policies (Henderson and Mason 2005).

Chong et al. (2015) examine the question of whether (and how many) vehicles with basic life support (BLS) should be deployed alongside the more traditional vehicles that carry advanced life support (ALS) equipment. The latter can treat a wider range of patient conditions but are more expensive to operate. Numerical experiments based on two complementary optimization models suggest that ALS-only systems perform comparably to models that maintain a combination of the two types of vehicles. Therefore, one may conclude that there is no compelling operational reason to add BLS to an ALS-only system.

McLay and Mayorga (2013) and Nasrollahzadeh et al. (2018) develop optimization models to study the problem of ambulance dispatching decisions. McLay and Mayorga (2013) focus on how to optimally prioritize patients and how to dispatch ambulances to meet specific equity constraints for patients and ambulance staff. The authors study the impact of the equity constraints using two numerical examples from a real EMS system. One interesting finding is that, in some scenarios, it may be possible to simultaneously improve equity for both patients and ambulances. Nasrollahzadeh et al. (2018) focus on ambulance dispatching and relocation decisions. The authors use approximate dynamic to develop high-quality solutions. Using data from a real EMS system, they report that their policies can significantly reduce the expected response time and fraction of high-priority late calls compared to best available static benchmarks.

6. Pharmaceutical Industry Operations

The pharmaceutical industry engages in research and development, manufacturing, and marketing of pharmaceutical drugs and vaccines that aim to prevent, cure, or slow down the progression of disease and alleviate symptoms. The global market for pharmaceutical products was worth $935B in 2017[6] and developed countries spend between 7–29% of their healthcare expenditure on drugs.[7] The industry is heavily regulated, with strict laws governing drug testing for safety and efficacy, and subject to various regulatory restrictions regarding marketing.

This section provides a review of research that examines operational decisions relating to clinical trials and the production of influenza (flu) vaccines. Work examining coordination issues that arise between parties participating in the supply chain of pharmaceutical drugs and vaccines will be reviewed in §7.3.

6.1. Clinical Trials

Before a new drug is approved it needs to undergo a series of staged clinical trials. These tend to be expensive, time-consuming, and often lead to failure (DiMasi et al. 2016, Savva and Scholtes 2014). Kouvelis et al. (2017) use a dynamic program to help guide the decisions of a pharmaceutical firm during the most expensive Phase III clinical trials on how many test sides to operate and how many patients to enroll in each side. The authors use data from past clinical trials to show that their model provides significant value.

6.2. Production of Influenza Vaccines

Influenza is a contagious respiratory illness caused by influenza viruses. CDC estimates that during the 2017–18 season 48.8 million people got sick with influenza leading to 959,000 hospitalizations and 79,400 deaths. Flu vaccine has been shown to be one of the most effective ways to reduce the disease burden. Manufacturing lead time for the vaccine is at least six months; hence, the influenza viruses in the seasonal flu vaccine are selected each year prior to the knowledge of actual strains, based on surveillance data and forecasts about which viruses are the most likely to circulate during the coming season.

Deo and Corbett (2009) develop a descriptive model that captures competitive interactions to show that yield uncertainty, a characteristic associated with influenza vaccine production, may be a contributing factor to the concentrated supply of vaccines that often leads to product shortages. In a complementary paper, Cho (2010) studies the influenza vaccine composition decision and develops guidelines based on dynamic programming for improving these decisions and their impact on vaccine availability and effectiveness.

7. Healthcare System Operations

Shifting attention from within hospital/clinic operations to the system level, the research reviewed in this section models operational decisions focused on the production, procurement, or allocation of limited resources (e.g., vaccines, deceased donor organs) and incentives in healthcare systems (e.g., hospital reimbursements, pharmaceutical supply chain contracts).

7.1. Infectious Disease Management

There have been significant medical advances in infectious disease prevention and control. However, infectious diseases still prevail, at times leading to outbreaks, epidemics, or pandemics. They can be transmitted from person to person (e.g., influenza, tuberculosis), can infect a person via bites from insects or animals (e.g., malaria, Lyme disease), or are acquired by ingesting contaminated food or water or other exposures in the environment (e.g., cholera). The following four papers provide prescriptive advice on how to allocate scarce resources to better manage infectious diseases.

Ekici et al. (2013) collaborated with the American Red Cross to study food distribution to affected patients following a severe influenza pandemic. While food distribution provides relief to the large population of affected patients and their families, the authors also study intervention strategies, such as voluntary quarantine, which help slow down the spread of the disease. The authors develop a model that forecasts the pattern of the disease spread geographically and over time, which they combine with a facility location and a resource allocation network model. They also develop near-optimal heuristics and demonstrate how their model could be used for the state of Georgia.

Looking at infectious diseases in the developing world, Long et al. (2018) examine outbreaks of Ebola, a high-mortality viral disease. The authors combine a novel dynamic disease-transmission model, which produces localized forecasts of new cases, with four optimization models that assign the limited amount of Ebola treatment units to different regions. The authors show that this methodology can help policymakers allocate the scarce resources more effectively by anticipating where the outbreak is moving next.

Deo and Sohoni (2015) develop an optimization model to determine where to deploy a limited number of point-of-care HIV diagnostic devices. These devices offer a quick method of diagnosing HIV infection in infants born to HIV-infected mothers. In 2017, there were approximately 36.9 million people (180K of them children) worldwide living with HIV/AIDS, with about 5,000 new infections per day.[8] Children are often infected by their HIV-positive mothers during pregnancy, childbirth or breastfeeding. While 75% of people living with HIV were aware of their status, others still need access to HIV testing services, which is essential for prevention and treatment. Using a detailed simulation model, the authors show that the deployment suggested by their optimization model can result in a large increase in the number of patients collecting their results, and that point-of-care devices are much more effective than other operational improvements in promoting early HIV diagnosis. Moving from HIV diagnosis to HIV/AIDS treatment in a resource-limited setting, Khademi et al. (2015), present a methodology for quantifying the cost associated with a policy where a patient remains under treatment until death. Since patients develop resistance to treatment over time, not terminating treatment implies that other patients, for whom the drugs would be more effective, may not be able to get treatment due to limited resources. Using approximate dynamic programming to optimize the decision about when to terminate treatment, the authors show that shifting to a policy that terminates treatment can increase the overall benefit of treatment by 4.4%–8.1%.

7.2. Organ Transplants

In the US, there are more than 113,000 people on the national transplant waiting list, while 36,528 transplants were performed in 2018; given the increasingly large gap between organ demand and supply, 20 people die each day waiting for a transplant.[9]

Two papers published in *M&SOM* focus on operational decisions associated with organ transplants. Su and Zenios (2004) develop a queueing game to study the organ–patient offer process. In their model a large number of patients are on a the waitlist for a kidney transplant. When a deceased donor kidney becomes available, it is offered to a patient at the top of the list, where the prioritization of the list is dynamically updated as a new organ becomes available, considering the donor, organ, and patient characteristics. If the patient declines the organ, it is then offered to the next highest patient on the list, and so on. The authors show that the current organ offer process encourages too many declines of organs that are of marginal (but still viable) quality as the patient first in line for transplantation has little to lose if they reject the first organ offered to them because they are likely to be first in line for the next organ that could be of higher quality.

Given that organs are viable for transplant for a limited amount of time, some organs reach the time limit after multiple offers and declines, and are eventually discarded. In the US, about 10 kidneys are discarded daily. The authors show that an alternative offer process would better align incentives, reduce waste, and thus increase the supply of organs.

Turning to kidney transplants from live donors, Glorie et al. (2014) study kidney exchanges that allow incompatible patient–donor pairs to exchange kidneys so the involved patients can receive a transplant. Unlike most previous research, the authors consider multiple criteria (e.g., medical compatibilities, number of transplants), which may lead to the inclusion of longer cycles or chains (with more than 2-3 pairs) in the solution. Existing branch-and-price type approaches face challenges in this setting since the solution of the pricing problem may take a long time. The authors present an iterative polynomial time branch-and-price algorithm and propose a polynomial time algorithm for the pricing problem to effectively handle multiple criteria. Their approach is demonstrated by using simulations with kidney exchange data from the Netherlands and the US.

7.3. Strategic Interactions and Incentives in Healthcare Systems

Maintaining and improving the health and quality of life requires the participation, interaction, and collaboration between multiple and diverse entities. Research published in *M&SOM* has looked at coordination decisions between payers (e.g., Centers for Medicare & Medicaid Services or private insurance firms in the US, the National Health Service in the United Kingdom) and outpatient clinics, healthcare providers, vaccine manufacturers, and participants in the pharmaceutical drug supply chain. In all of these interactions the different stakeholders have multiple and often conflicting objectives. Hence, with the goal of coordinating a complex decentralized system, it is important to understand the objectives of different players and design appropriate incentives, for example, through payment, reimbursement, or contracting mechanisms. In a well-functioning and adaptive healthcare system, incentives are "aligned to encourage continuous improvement, identify and reduce waste, and reward high-value care."[10]

In the context of outpatient clinics, Jiang et al. (2012) develop a principal–agent model to examine the decision to allocate time slots between open-access and traditional appointments (see §2). In their model, the principal (e.g., the payer) needs to incentivize the provider (e.g., the outpatient clinic) to provide a sufficient number of appointments to achieve a certain patient waiting-time target. The authors show that simple fee-for-service or performance-based schemes (where the provider's payoff is decreasing in patient waiting time) do not achieve the first-best outcome and, instead, the principal needs to set non-linear performance-based contracts.

Guo et al. (2019) study healthcare provider reimbursement, examining the impact of two reimbursement schemes used in practice, fee-for-service and bundled payment, on social welfare, patient revisit rate, and patient waiting time. Under the first scheme, providers receive a payment each time a patient visits (or revisits) the provider, while under the second, the provider receives a fixed fee regardless of the number of (re)visits. The authors formulate a model where patients' revisit rate decreases in the providers' service time (quality-speed trade-off) to show that for sufficiently large patient pools, the bundled payment scheme dominates the fee-for-service scheme in all measures.

Dai et al. (2016b) study contracts that motivate on-time delivery of influenza vaccines. The authors show that, due to yield uncertainty, as well as uncertainty over the final vaccine composition described by Cho (2010) (see §6.2), the relatively simple contracts that are commonly used in practice fail to coordinate the supply chain. The authors propose more complex contracts that have the ability to restore first best.

Turning to pharmaceutical supply chains, Zhao et al. (2012) study the impact of the relatively recent fee-for-service contracts on the way the pharmaceutical distribution supply chain is designed, managed, and operated. In contrast to the 'forward buying' model, which was the norm in the past, the authors show that with carefully-designed contract parameters fee-for-service contracts lead to a Pereto improvement. Hu et al. (2012) and Kouvelis et al. (2015) use game-theoretic models to study the impact of intermediaries on the efficiency of the healthcare-product/pharmaceutical supply chain. The first paper focuses on the functions of a group purchasing organization, an intermediary between profit-maximizing manufacturers and multiple cost-minimizing healthcare providers (e.g., hospitals). The second paper's focus is on multiple competing pharmacy benefit managers (PBMs) that need to make pricing and 'formulary' decisions (assign branded drugs to preferred or non-preferred tiers). In both papers, the authors provide characterization of supply chain performance and relevant insights for policymakers considering the characteristics of the pharmaceutical supply chain.

8. Medical Decision-making

Papers on medical decision-making published in *M&SOM* develop mathematical models, mainly utilizing queuing or Partially Observable Markov Decision Process models, to provide physician guidelines on disease screening, diagnosis, and treatment, or to understand the drivers behind certain physician behaviors, such as excessive test ordering.

Screening of asymptomatic individuals (possibly followed with a diagnostic procedure, depending on screening results) can diagnose disease at earlier stages and increase the chances of treatment success (Ayer et al. 2014). While screening benefits a small percentage of the population who have the disease, it is costly, and the majority of the remaining population receives little or no direct benefit, or even may be exposed to physical or emotional harms, for example, due to false-positive results, leading to stress, unnecessary follow-up procedures, or overtreatment. Hence, governments and healthcare systems need to carefully evaluate screening guidelines considering patient needs and efficient allocation of medical resources. Four papers published in *M&SOM* develop such guidelines. Erenay et al. (2014) create personalized guidelines for colorectal cancer screening and Lee et al. (2018) develop screening guidelines for patients at risk of hepatocellular carcinoma. Zhang et al. (2012) create personalized guidelines for biopsy referral decisions for prostate cancer and Ayvaci et al. (2012) develop guidelines for further diagnostic tests following mammography.

To complement the previous papers that focus on screening, the work of Skandari et al. (2015) focuses on treatment. It provides guidelines on which vascular access to use, namely, the arterio-venous fistula or the central venous catheter, for patients undergoing hemodialysis. The former is considered better for patients but more complicated to perform compared to the latter.

In many healthcare systems, a substantial portion of testing and treatment is deemed unnecessary, leading to waste and little to no improvement in health outcomes. In the US, unnecessary services, including overuse beyond evidence-established levels, discretionary use beyond benchmarks, and unnecessary choice of higher-cost services, lead to an estimated $210 billion in excess cost.[11] Dai et al. (2016a) develop a strategic queueing framework to examine the operational, clinical, and financial drivers behind physician test-ordering behavior in an eye center. Their results provide a more nuanced understanding on the impact of patient co-payments, insurance coverage, external reimbursement ceilings, and concerns about misdiagnosis, and the phenomenon of over-testing.

Medical decisions directly impact on the outcomes for individual patients, and they indirectly impact the resource utilization, and in turn, access to care for a broader group of patients. Ormeci et al. (2015) develop a modeling framework for outpatient clinics (e.g., colonoscopy services) that provide both screening (preventive) and diagnostic (repair) services. In their model, demand is stochastic and (partially) endogenous: more screening services reduce future demand for diagnostic services. The authors develop guidelines based on dynamic programming on how to manage the trade-off between urgent diagnostic patient needs and non-urgent screening needs.

9. Opportunities for Future Research

There are tremendous opportunities for developing and applying OM methods to make a positive impact in healthcare. This view is shared by OM scholars and medical practitioners. For example, in a recent article published in *Lancet Infectious Diseases*, the authors support the use of operations research models "to improve programme outcomes in relation to medical care or prevention, to assess the feasibility of new strategies or interventions in specific settings or populations, and to advocate for policy change" (Zachariah et al. 2009, p. 713). The research discussed in the previous sections offers some concrete examples. In this section we suggest a non-exhaustive list of further opportunities.

9.1. New Solutions for Old Problems

Healthcare organisations have always had to make decisions that were amenable to mathematical description, usually in the form of optimization or queueing problems. Examples include appointment and operating room scheduling, staffing and rostering, patient routing, ambulance dispatching, bed management, and clinical trial design. OM research has developed approximations and bespoke algorithms to provide insights and decision support tools for these difficult problems. With more data becoming available and improved computational power, there is now an opportunity to create new types of solutions. Examples include data-driven algorithms that create patient, staff, or operating room schedules with provably good performance (Ban and Rudin 2018, Begen et al. 2012), dynamic protocols for the design of clinical drug trials (Chick et al. 2018) or for predicting their outcome (Bertsimas et al. 2016), or novel and more equitable designs of organ transplant protocols (Bertsimas et al. 2013).

9.2. New Models for Old Problems

Further to developing better solutions, there is scope for research to develop new models that capture a more nuanced perspective of healthcare problems by incorporating important real-world features that have been overlooked. Examples include:

- In the context of the ED, new models are needed that inform capacity and staffing decisions that explicitly consider: i) the endogeneity between service times, congestion, and patient demand; ii) equity in waiting time, for example by minimizing the proportion of patients who wait four hours or more (Green and Soares 2007); iii) interconnectedness between EDs, hospital wards, and ambulance stations, where congestion in one part of the system may compromise the performance of other parts. For example, a leading cause of ambulance diversion is the phenomenon of patient boarding, where ED patients in need of admission to an inpatient bed continue to occupy ED beds because of congestion in hospital inpatient wards (Allon et al. 2013).
- For patient appointment scheduling, new models could take into account: i) appointment type, duration, and resources needed, which can vary significantly across appointments; ii) patients' preferences over different appointment dates; iii) potential future arrivals and current commitments in the system; iv) alternative service disciplines (e.g., proactive service (Delana et al. 2019)); v) patients' needs that may include multiple services with some dependencies from different providers over multiple days, for example as in infusion centers or rehabilitation facilities for spinal cord injuries (Arsik et al. 2017).
- Emergency services dispatch decisions would benefit from novel models that coordinate more than one emergency services. For example, during Hurricane Harvey, paramedics had difficulties reaching patients' homes due to flooding and depended heavily on the availability of boats from an independent water rescue unit.

- New models of infectious disease management that synergistically bring together disease modeling approaches from epidemiology, with resource allocation approaches from operations management to treat, prevent, or slow down disease transmission and spread.
- New models for blood inventory management that explicitly tackle the uncertainty of supply caused by the fact that most blood is collected from volunteer donors. Such models could combine decisions on inventory management, donor recruiting, and collection strategies to better match demand and supply.

9.3. New Models for New Problems: Personalized Medicine and Digital Health

New technologies are becoming available to support personalized medicine. For example, wearable devices monitor activity and vital signs of thousands of active users. This wealth of information, combined with teletriage/telemedicine technology that lowers the cost and reduces the time-lag in accessing care, could be used to promote prevention, monitor compliance with treatment, enable proactive interventions, etc. The OM community could contribute by developing algorithms that allow to exploit the trove of data, redesign patient pathways to exploit this information, and investigate their cost effectiveness.

More broadly, there is an opportunity to use OM methods (e.g., optimization, simulation, machine learning) to create a new class of personalized decision support tools. For example, IBM's Watson Oncology product takes as input a patient's medical records, develops a personalized treatment plan, and suggest which treatments should not be pursued, aiding clinicians on patient-levels decisions based on the latest available research.[12] This is part of a wider trend. The Food and Drug Administration in the US has approved 12 algorithms for limited clinical use and is in the process of creating dedicated regulatory pathways for digital health.[13] Similarly, in the case of organ transplants, analytics-based decision-support tools could help patients and physicians evaluate the trade-offs between accepting an organ offered versus remaining on the waitlist in the hope of receiving an offer for a better quality organ in the future (Mark et al. 2019).

9.4. Models for Aligning Incentives and Integrating Care

Healthcare systems in the developed world, and especially the US, are extremely fragmented (Dai and Tayur 2018), and providers are largely reimbursed based on activity with few, if any, incentives for cost reduction, improvement of clinical quality, coordination across different providers, or, indeed, prevention (Green 2012). Tools to manage the system's complexity are inadequate or do not exist at all (Stead et al. 2009). OM models, and in particular the combination of systems-thinking and economic theory can help identify and rectify inefficiencies by better aligning incentives, designing integrated patient-care processes, and by coordinating resource allocation decisions at different levels of the care ecosystem.

Aligning incentives in hospital care. Hospital reimbursement and regulation had focused predominately on cost containment through the prospective payment system developed by Fetter (1991). Emphasis is now shifting on improving quality. The OM community can develop models that generate insights as to how to augment existing practice to achieve better outcomes, such as reducing waiting times (Savva et al. 2019) or curtailing hospital readmissions (Arifoglu et al. 2018).

Better integrated patient-care. At least some ED visits are the result of inadequate access to primary or community-based care, or due to poor choices on the part of patients, and thus are entirely preventable. For example, in the US, the number of preventable visits is estimated to be 13%–27% costing $4.4 billion annually.[14] The OM community could develop data-driven methods to identify geographic areas or communities where primary care is failing and investigate how investments or other improvements in one part of the system, or initiatives that aim to better coordinate acute hospital care with preventative and chronic care in the community (e.g., the patient-centered medical home[15]), can impact on the overall cost, access to care, and health outcomes.

New care models. As we experiment with alternative value-based reimbursement models, such as those mandated by the Affordable Care Act of 2010, it is important to use models to assess the economic and operational implications of proposed changes and identify potential unintended consequences. For example, Accountable Care Organisations provide incentives to a network of independent providers to improve the quality of care and reduce costs for specific patient conditions (e.g., joint replacement), and the Hospital Value-Based Purchasing Program adjusts hospital payments based on the quality of care.[16]

Coordinating resource allocation. Another opportunity is for analytical models to investigate the interface between medical decisions and operational efficiency. More specifically, it would be useful to develop data-driven guidance on how to sensibly trade-off the competing objective of doing what is clinically best for the patient against what is best for the system. Examples include decisions around antibiotic prescription (which will need to trade-off the benefit for the individual with the risk of increasing antibiotic resistance in the population) and decisions around diagnostic/treatment guidelines under resource constraints (Ayvaci et al. 2012). **Public health.** Beyond treating acute illness, the impact of public and population health can be as significant in keeping the population healthy for longer. Furthermore, interrelationships among the determinants of health, i.e., personal, social, economic, and environmental factors, cross the boundaries of traditional healthcare and public health into sectors such as education, housing, transportation, agriculture, and environment, and play a role in improving population health.[17] OM researchers can help design and evaluate integrative health systems and operational strategies, putting the patient at the center and considering physical, emotional, mental, social, spiritual, and environmental factors impacting health.

9.5. Impact on Practice

We note that despite the abundance of research in operations management providing prescriptive advice or guidelines, the use of these methods in practice is still limited. A number of factors contribute to this – the methods may be too complex to implement, or make assumptions that do not always hold in practice, or because the proposed approaches require a major shift in care/provider practice and culture. Another challenge for researchers is the availability and access to data. For example, in the case of appointment scheduling, many clinics have data about the actual schedule, but often do not have data on the requested (versus actual) date/time of the appointment, patient arrival time, or the actual duration of the appointment.

Some notable exceptions discussed in this review, (e.g., Ayer et al. (2019), Ekici et al. (2013), Ozen et al. (2015)) suggest that translating research to practice is possible. To increase the impact of our field in practice, we hope to see closer collaborations between OM researchers and practitioners in health systems, data-driven models that are not only mathematically elegant but also capture the salient aspects of practical decisions and related factors, and user-friendly decision-support tools that embed the developed models to aid practitioners in patient-level as well as operational or system-level decisions.

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