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REVIEW ARTICLE

Mind the gap: a review of optimisation in mental healthcare service delivery

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ABSTRACT
Well-planned care arrangements with effective distribution of available resources have the potential to address inefficiencies in mental health services. We begin by exploring the complexities associated with mental health and describe how these influence service delivery. We then conduct a scoping literature review of studies employing optimisation techniques that address service delivery issues in mental healthcare. Studies are classified based on criteria such as the type of planning decision addressed, the purpose of the study and care setting. We analyse the modelling methodologies used, objectives, constraints and model solutions. We find that the application of optimisation to mental healthcare is in its early stages compared to the rest of healthcare. Commonalities between mental healthcare service provision and other services are discussed, and the future research agenda is outlined. We find that the existing application of optimisation in specific healthcare settings can be transferred to mental health-care. Also highlighted are opportunities for addressing specific issues faced by mental health-care services.

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Mental healthcare; service delivery; optimisation; planning; COVID-19

1. Introduction

Mental health is a significant global concern, not only for public health but also for economic development and societal welfare. Mental health disorders are on the rise around the world. Failure to respond to this growing crisis could cause lasting harm to individuals, societies and economies worldwide. This crisis has been exaggerated by the COVID-19 pandemic (Pfefferbaum & North, 2020). The gap between the need for treatment and its provision is a global issue. The World Health Organisation (WHO) estimates that between 35% and 50% of people with severe mental health problems in developed countries and 76–85% in developing countries receive no treatment (World Health Organization, 2019). Untreated mental health problems account for 13% of the total global burden of disease (Ibid). Concern for mental health as a pressing public health issue is also building as the magnitude of the problem is put in economic terms. The World Economic Forum estimates that the costs associated with mental illness at $2.5 trillion in 2010 can grow to $6 trillion in 2030 (Bloom et al.,). Mental illness costs exceed the cost of any other non-communicable disease, including cardiovascular disease, chronic respiratory disease, cancer, and diabetes (McDaid et al., 2019).

At present, as the world confronts the COVID-19 pandemic, experts predict a looming mental health crisis on the horizon (Sangeeta et al., 2020). Before COVID-19 emerged, statistics on mental health conditions were already stark. As the situation unfolds, there is emerging evidence that healthcare workers are at significant risk of adverse mental health outcomes (Ho et al., 2020; Kang et al., 2020; Lai et al., 2020). For patients living with existing mental health challenges, the pandemic carries a high risk of symptoms worsening, mental or emotional deterioration or full-blown relapse (Yao et al., 2020). This constantly changing landscape has increased levels of loneliness, depression, harmful alcohol and drug use, and self-harm or suicidal behaviour (World Health Organization, 2020). Globally, the pandemic has exposed glaring health disparities and highlighted the weaknesses in seemingly robust healthcare systems (Tandon, 2020). Simultaneously, the pandemic has highlighted the significance of mental health and the pressing need for parity with other health services (Moreno et al., 2020). While several initiatives to strengthen mental health services have sprung up, the response has been hampered by the historical underinvestment (United Nations, 2020). The COVID-19 pandemic is markedly a turning point, moving mental health up the list of global health priorities. As countries struggle to rebuild their damaged economies, they are being urged to accept the reality of the financial toll of mental ill-health and invest in efficient and good quality services (The Lancet Global Health, 2020).

Operational Research (OR) encompasses a wide range of problem-solving techniques and algorithms that are applied in the pursuit of improved decision-making and efficiency. Over the last two decades, OR methodologies have been applied extensively to various health care systems. In contrast, the mental/psychological care services have been noted as an area of neglect in OR (Bradley et al., 2017). For instance, existing reviews explore the application of specific

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OR methodologies, such as simulation (Langellier et al., 2019; Long & Meadows, 2018; Noorain et al., 2019), and Data Envelopment Analysis (García-Alonso et al., 2019), on mental healthcare services. In contrast, a comprehensive review of the application of optimisation methodologies to mental healthcare in the OR literature is lacking. We aim to provide a comprehensive and up-to-date account of the application of optimisation for planning and delivery in mental/psychological healthcare services.

The contributions of this review are threefold. First, we provide a comprehensive overview of the application of optimisation in healthcare so far. Through this, we highlight gaps in existing optimisation literature and examine future research directions. Second, we analyse the context of mental healthcare services to identify unique features and investigate if similar features have been considered in the healthcare literature. Our primary contribution though results from a scoping review on the application of optimisation techniques in mental healthcare services to identify issues for researchers to analyse, study and model.

The remainder of this paper is organised as follows. Section 2 provides background information on the topic by examining existing optimisation literature in healthcare and analysing the context of mental healthcare services. Section 3 describes the search methodology employed in this review, followed by Section 4, which provides a thematic overview and presents an analysis of optimisation model components such as the objective function, model constraints, model formulation and solutions methodologies employed by the articles under review. Section 5 draws on the similarities between mental healthcare services and other healthcare settings and sets the agenda for future research. Section 6 presents some conclusive remarks.

2. Background

This section is intended to serve four purposes: to provide a brief overview of planning levels, to describe the components of an optimisation model, to illustrate the use of optimisation in healthcare, to demonstrate the unique characteristics of mental illness, and to explore opportunities of synergy between the application of optimisation and mental healthcare services.

2.1. Planning levels

The optimisation literature is often organised based on four hierarchical planning levels, including various planning decisions (Cissé et al., 2017; Hans et al., 2012). The four hierarchical levels are strategic, tactical, operational offline, and operational online (Hulshof et al., 2012). Planning on a strategic level addresses structural decisions with a long planning horizon, whereas planning on a tactical level involves the translation of strategic planning decisions into guidelines that facilitate operational planning (Hans et al., 2012). Operational planning involves short-term decision-making, reflecting the execution of tactical blueprints. Offline operational is about *advance* planning or operations, whereas online operational planning deals with reactive decision making in response to events that cannot be planned in advance (Cardoen et al., 2010; Hulshof et al., 2012).

2.2. Optimisation model

There are three main components in an optimisation model: objective function, decision variables, and constraints. An optimisation model seeks to find the values of decision variables that optimise (maximise or minimise) an objective function among a set of values of the decision variables that satisfy given constraints (Winston & Goldberg, 2004). To illustrate, consider a simplified example. A hospital emergency room would like to minimise costs associated with scheduling nurses. The optimisation model would include the "objective function" (goal) to minimise costs related to nurses. The "decision variable" would be the number of nurses to be deployed and, the "constraints" would be the limits on the number of nurses required for a shift.

The optimisation model is formulated using a wide range of prominent techniques, including linear programming (Dantzig, 1951), integer programming (Wolsey & Nemhauser, 1999), dynamic programming (Bellman, 1966), stochastic programming (Kall et al., 1994), network programming (Bertsekas, 1991), combinatorial optimisation (Wolsey & Nemhauser, 1999), and nonlinear programming (Bazaraa et al., 2013). The type and complexity of a model will dictate the solution method of choice. Exact algorithms such as simplex (Dantzig et al., 1955), branch and cut (Padberg & Rinaldi, 1991), and branch and bound (Little et al., 1963) are employed to solve optimisation problems to optimality. If a model is too complex to be solved by exact algorithms, the search for an optimal solution is abandoned to seek a reasonable solution using heuristics or metaheuristics. Heuristics and metaheuristics use a collection of intelligent rules of thumb to find a suitable solution quickly (Horst & Pardalos, 2013). Examples include column generation heuristic (Taillard, 1999), Tabu Search (Glover, 1986), and simulated annealing (Kirkpatrick et al., 1983).

2.3. Optimisation in healthcare

A survey of recent literature reviews on the application of optimisation techniques in healthcare is presented in this section. Articles were identified on Scopus, and then a backward search was performed using the initial pool of papers to find additional reviews. We selected review articles for analysis if they were published in the period (2011–2019) and analysed the application of OR methodologies to planning issues in healthcare. In the past decade, 19 literature reviews on the application of Operations Research/ Management (OR/OM) in healthcare have been published. These include reviews that are generic and specific in their scope. Generic reviews examine the nature of the application of OR/OM techniques to healthcare (Brailsford & Vissers, 2011; Hulshof et al., 2012; Rais & Vianaa, 2011). In contrast, specific reviews are spread across application areas such as planning and scheduling, routing and scheduling, and supply chain management.

This analysis is primarily concerned with surveying articles that review research that has applied optimisation techniques in healthcare. Therefore, reviews with a specific scope are given preference. These include review articles from various application areas – specifically, nine reviews on planning, scheduling and routing and six on supply chain management. We build a comprehensive picture of the optimisation landscape in healthcare to identify the progress so far, highlight gaps and analyse the direction of future research. Table 1 depicts critical gaps and limitations specified in each research area that were identified in each review article.

2.3.1. Planning, scheduling & routing

In healthcare, planning, scheduling & routing decisions have been explored extensively. We classified reviews into several themes based on the area of research. We find that the planning of operating rooms has received the most attention (Cardoen et al., 2010; Samudra et al., 2016; Zhu et al., 2019), followed by routing and scheduling in home healthcare (Cissé et al., 2017; Fikar & Hirsch, 2017; Gutiérrez & Vidal, 2013). We also identified reviews on physician scheduling (Erhard et al., 2018) and appointment scheduling (Ahmadi-Javid, Jalali, et al., 2017). Furthermore, we also include reviews on two budding research areas, namely the multi-appointment scheduling problems in hospitals (Marynissen & Demeulemeester, 2019) and multi-disciplinary planning and scheduling (Leeftink et al., 2020). Based on this classification, an analysis of literature reviews is presented in this section.

2.3.1.1. Operating room planning & scheduling. Operating theatres are a hospital's most significant cost and revenue centre, with substantial impacts on a hospital's performance as a whole (Macario et al., 1995). Several reviews have examined the literature on operating room planning and surgical care scheduling (Cardoen et al., 2010; Samudra et al., 2016; Zhu et al., 2019). This literature primarily deals with two categories of patients, namely elective or non-elective and inpatient or outpatient. Furthermore, operating room planning and surgical scheduling address a variety of issues, including the determination of resource quantity (surgeons, nurses, rooms, equipment, operations time) needed to meet demand; allocation of operating room capacity to various medical disciplines; assigning definite dates for operations; determining the start time of the operations and the allocation of resources. Zhu et al. (2019) observe that most research has been directed towards scheduling problems at the operational level (Kroer et al., 2018; Roshanaei et al., 2017). Moreover, Samudra et al. (2016) notice that a large part of the literature is aimed at decision-making on a patient level (Agnetis et al., 2012). Particularly to the assignment of dates and room (Banditori et al., 2013).

Performance measures are primarily in the interest of the three stakeholders in the system: hospital administrators, medical staff, and patients (Wachtel & Dexter, 2009). Consequently, performance measures that are considered as model objectives were financial, utilisation, levelling (resource occupancy), throughput, idle time, makespan (completion time), preferences, waiting time, and patient deferrals. Likewise, uncertainty related issues are a significant component of operating room planning and scheduling. Therefore, models account for uncertainties relative to surgery duration (deviation between actual and planned) (Denton et al., 2007), patient arrival (unpredictable arrival of outpatients) (Beliën et al., 2009), resources (availability, applicability and usability of human and material resources) (Cardoen et al., 2010), and more recently, uncertainty relative to care requirement (Holte & Mannino, 2013). The most considered type of uncertainty in models is duration uncertainty, followed by arrival uncertainty. Although the arrival of non-elective patients generates significant operational deficiencies, few studies have modelled this (Arenas et al., 2002; Pham & Klinkert, 2008). Generally, planning and scheduling of elective patients has received more attention when compared to non-elective and outpatients (Lamiri et al., 2009). This trend in research is despite the ongoing shift from inpatient to outpatient care (Koenig & Gu, 2013).

2.3.1.2. Physician scheduling. Shortages in medical personnel are ubiquitous in most industrialised countries. The scarcity of physicians adds increasing pressure on managers to find efficient and effective ways to schedule their workforce. Therefore, physician scheduling has received a fair amount of attention over the last decade. Erhard et al. (2018) surveyed physician scheduling in hospitals by classifying them as problems of staffing (determining size and composition), rostering (creating shift rosters), and re-planning (short-term adjustments to schedules). Research in this area mainly concentrates on building mid-and long-term rosters (Bruni & Detti, 2014; Brunner &

Table 1. Key Future Research Directions from Optimisation Related Literature Reviews.

	Publication	Key Future Research Directions
Planning & Scheduling	**Cardoen, B., Demeulemeester, E. and Beliën, J., 2010. Operating room planning and scheduling**: A literature review. *European Journal of Operational Research*,*201*(3), pp.921–932.	• Account for stochastic activity duration. • Research non-elective patient scheduling • Model integrated facilities & resources
	Samudra, M., Van Riet, C., Demeulemeester, E., Cardoen, B., Vansteenkiste, N. and Rademakers, F.E., 2016. Scheduling operating rooms: achievements, challenges and pitfalls. *Journal of Scheduling*, 19(5), pp.493–525	• Consideration of stochastic arrivals & patient bulking (leaving waiting list) • Research on outpatient and non-elective. • Inclusion of behavioural factors as performance measures. • Model integrated system (outpatient & inpatient) • Apply stochastic programming for real-life problems.
	Ahmadi-Javid, A., Jalali, Z. and Klassen, K.J., 2017. Outpatient appointment systems in healthcare: A review of optimisation studies. *European Journal of Operational Research*,*258*(1), pp.3–34.	• Models to incorporate continuity of care, patient preferences, patient walk-ins. • Models to include environmental variables (no-shows, patient & physician unpunctuality). • Consider environmental factors such as disruption (natural disasters, economic or financial crises, social events) • Develop novel multi-decision models to address real-life situations.
	Erhard, M., Schoenfelder, J., Fügener, A. and Brunner, J. O., 2018. State of the art in **physician scheduling.** *European Journal of Operational Research*,*265*(1), pp.1–18.	• Estimation of realistic demand and demand fluctuation. • Models to incorporate physician absenteeism and break assignment • Consider simulation-optimisation as an alternative solution approach. • Models to develop flexible shifts.
	Leeftink, A.G., Bikker, I.A., Vliegen, I.M.H. and Boucherie, R.J., 2018. Multi-disciplinary planning in health care: a review. *Health Systems*, pp.1–24.	• Account for variability in the care pathway and resource capacity with stochastic or robust programming • Model multi-disciplinary care outside hospitals. • Explore applicability of methods across health areas
	Marynissen, J. and Demeulemeester, E., 2019. Literature review on **multi-appointment scheduling** problems in **hospitals.** *European Journal of Operational Research*, 272(2), pp.407–419.	• Account for emergency patients in inpatient and outpatient scheduling by reserving capacity. • Monitor and report system performance before and after implementation • Report on implementation.
	Zhu, S., Fan, W., Yang, S., Pei, J. and Pardalos, P.M., 2019. Operating room planning and **surgical case scheduling**: a review of literature. *Journal of Combinatorial Optimisation*,*37*(3), pp.757–805.	• Models to incorporate stochastic surgical duration. • Research non-elective patient scheduling • Focus on resource (human and material resource) uncertainty • Focus on uncertain medical requirements by patients.
Routing & Scheduling	**Cissé, M., Yalçındağ, S., Kergosien, Y., Şahin, E., Lenté, C. and Matta, A., 2017**. OR problems related to **Home Health Care**: A review of relevant **routing and scheduling** problems. *Operations Research for Health Care*,*13*, pp.1–22.	• Capture uncertainty aspects (travel time between locations, care service duration, emergencies, workers' or patients' unavailability) with stochastic models. • Account for cancellation of appointments or last-minute absence of care workers.
	Fikar, C. and Hirsch, P., 2017. Home health care routing and scheduling: A review. *Computers & Operations Research*, 77, pp.86–95.	• Models to consider emergencies, cancellation, unavailability of nurses & traffic delays. • Include ecological & social criteria.
Supply Chain Management	**Li, X., Zhao, Z., Zhu, X. and Wyatt, T., 2011**. Covering models and optimisation techniques for **emergency response facility location and planning**: a review. *Mathematical Methods of Operations Research*,*74*(3), pp.281–310.	• Models to incorporate different priorities requiring different types of services. • Models to consider survival rate as an objective function. • Incorporate equity in facility distribution.
	Gutiérrez, E.V. and Vidal, C.J., 2013. Home health care logistics management: Framework and research perspectives. *International Journal of Industrial Engineering and Management*, 4(3), pp.173–182.	• Model long-term resource location and allocation issues. • Integrated analysis of logistic decision across planning levels • Models to include realistic features (patient pathologies, service references & legal work regulations)
	Ahmadi-Javid, A., Seyedi, P. and Syam, S.S., 2017. A survey of **healthcare facility location.** *Computers & Operations Research*, 79, pp.223–263.	• Dynamic location models accounting population migration, changes in management objectives, transportation & facility capacities, patient population. • Statistical methods to estimate input parameters. • Models to include multiple services and service quality. • Capture realistic assumptions such as uncertain & multi-type demand, & multiple servers.
	Volland, J., Fügener, A., Schoenfelder, J. and Brunner, J. O., 2017. Material logistics in hospitals: a literature review. *Omega*, 69, pp.82–101.	• Heuristics to address large-scale, real-life complex logistics problems. • Improve and incorporate forecasting mechanism to capture demand. • Employ optimisation to determine product characteristics or to define an optimal degree of outsourcing. • Models to incorporate lead times.
	Ahmadi, E., Masel, D.T., Metcalf, A.Y. and Schuller, K., 2019. Inventory management of **surgical supplies and sterile instruments** in **hospitals**: a literature review. *Health Systems*,*8*(2), pp.134–151.	• Stochastic models to incorporate operational and/or disruption risk factors. • Models to incorporate stochastic demand for instruments. • Models to determine location and quantity of supplies to stock. • Consider inventory cost and service levels simultaneously.
	Saha, E. and Ray, P.K., 2019. Modelling and analysis of **inventory management systems in healthcare**: A review and reflections. *Computers & Industrial Engineering*, p.106051.	• Develop integrated model considering all types of medical products should be considered (e.g., pharmaceuticals, medical equipment, surgical instruments). • Heuristics to consider randomness and complexities (patient arrivals, illness, treatment stages, treatment responses). • Model uncertainty (demand for medicines, patient conditions, & physician prescribing behaviour) using robust optimisation and probabilistic programming.

Edenharter, 2011), thereby foregoing the incorporation of realism in models. Moreover, model objectives/goals are either financial (minimising wage costs, overtime, outside resource usage) or non-financial (minimising demand under coverage, roster changes and maximising employee preference). As for constraints, models consider two types, hard (non-negotiable) and soft (negotiable). Hard constraints are classified into two types: compulsory, including meeting demand, single shift per period, restricted backwards rotation, and minimum rest periods. At the same time, soft constraints are relative to ergonomics (preference, weekends off, days off, forward rotation, shift duration limits) and fairness (distribution of unpopular shifts, free weekends etc.). The most frequently used modelling methodologies are Integer Programming (Dexter et al., 2010), Mixed-Integer Programming (Bard et al., 2017) and Linear Programming (Topaloglu, 2009). As for solution algorithms employed to solve models, exact algorithms (Shamia et al., 2015) are preferred over heuristic algorithms (Samah et al., 2012). However, since demand cannot be fully controlled, using deterministic demands to generate schedules is noted as a drawback. Moreover, the review highlights the increasing willingness of hospitals to provide data and conduct experimental studies. Specifically, of the 68 studies, 64 used real life data to test the performance of the proposed theoretical model and 24 (more than a third) reported on the implementation results in hospitals (Erhard et al., 2018).

2.3.1.3. Appointment scheduling. Outpatient Appointment System (OAS) problems have been studied since 1952 (Bailey, 1952). An early review classified appointment systems into three categories based on their environment: primary care, speciality care and elective surgical care (Gupta & Denton, 2008. While surgeries can be scheduled as either inpatient or outpatient, the other two types are predominantly outpatient. Surgical/operating theatre scheduling is addressed in the above section, here we discuss appointment scheduling in primary care and specialist care (outpatient). In the latest and most up-to-date review of literature by Ahmadi-Javid, Jalali et al. (2017), it is observed that most OAS studies deal with operational decisions that are related to the execution of plans on an individual patient level. These include allocating of patients to servers/resources (Riise et al., 2016), determining appointment day and time (Chen & Robinson, 2014; Kuiper et al., 2015), patient acceptance/rejection (Qu et al., 2015), and patient selection from the waiting list (Saure et al., 2012). Furthermore, several studies also address problems at a tactical level, resulting in the determination of characteristics of the OAS that maximises resource utilisation and accessibility (Wiesche et al., 2017). Additionally, performance measures often pertinent to the three main stakeholders: patients, system owners and staff are used in OAS models. We also found that studies have used patient waiting time as a measure of patient satisfaction (Kemper et al., 2014), revenue is calculated as a measure of the number of patients seen (Balasubramanian et al., 2012), and costs are a measure of physician idle time (Vink et al., 2015). The most common performance measures used in OAS studies are the patient waiting time, staff idle time, overtime (Anderson et al., 2015), number of patients seen, number of patients rejected (Gocgun & Puterman, 2014). Although exact methods are used extensively, they are most often used to compare some given policy and develop efficient algorithms (Huh et al., 2013; Truong, 2015). Ergo, due to the complexity of OAS problems, most studies employ heuristic/metaheuristic/approximate methods (Anderson et al., 2015; Azadeh et al., 2014; Castro & Petrovic, 2012).

When compared to early review papers (Cayirli & Veral, 2003; Gupta & Denton, 2008, several milestones concerning future research have been achieved in this last decade. In particular, models now incorporate environmental factors such as patient preferences, cancellations, no-shows, and indirect patient waiting (time between appointment request and allocation) (Anderson et al., 2015; Erdogan et al., 2015). Although this area is growing and expanding, OAS has many open and complex research questions. For instance, Ahmadi-Javid, Jalali et al. (2017) advocate adopting more realistic assumptions relative to environmental factors. They also highlight the need to include interruptions (writing up notes, talking with support staff, or emergency patient arrivals) into existing optimisation models (Klassen & Yoogalingam, 2013; Luo et al., 2012). Along similar lines, the review also highlights the need to study the effects of disruptions to OASs. Specifically, disruptions relative to natural disasters (earthquakes, floods and terrorist attacks) likely result in very high-level demands of urgent walk-ins; disruptions caused by economic or financial crises; and social events that could result in complete stoppage or severely reduce the availability of resources.

2.3.1.4. Home Health care (HHC) routing & scheduling. Owing to a shifting trend in many countries where healthcare services are transitioning from a hospital setting to homes, HHC is a promising and growing research area (Genet et al., 2011). Providers of HHC dispense a range of services, including healthcare provider care, nursing, therapy (physical or occupational), medical social services, health aides, attendant care, volunteer care, nutrition and meal support, medical equipment and supplies, laboratory and pharmaceutical services, and transportation (John

Hopkins Medicine, 2020). Based on three planning levels (strategic, tactical and operational), several issues are addressed in literature: 1) partitioning of HHC service territory into patient clusters and assigning resources to each cluster; 2) identifying resource (people or materials) levels and assigning resources to districts, and 3) assigning care workers to patients and scheduling patient visits assigned to each care worker. Issues relative to HHC overlap considerably with the problems addressed in logistics (Gutiérrez & Vidal, 2013). Therefore, reviews focusing primarily on the operational level of decision-making are discussed (Cissé et al., 2017; Fikar & Hirsch, 2017). A broader logistics oriented review is analysed under supply chain management.

In the past decade, an increasing number of studies have addressed routing and scheduling issues in HHC (Cissé et al., 2017). The presence of certain salient features such as "full continuity of care", where a unique care worker visits a patient over a planning horizon, generate challenges when modelling the system. Despite the challenges associated with incorporating such features into a model, Cissé et al. (2017) find that most researchers use several of the above features in their model's objectives and constraints (Mankowska et al., 2014). Additionally, Fikar and Hirsch (2017) identify that most models are tested on data originating from real-world operations. However, the models have not considered uncertainty relative to travel time, care service duration, emergencies, and unavailability of workers or patients. Nevertheless, some studies consider uncertainties concerning when and where, in the future, patients will request care (Hewitt et al., 2016).

2.3.1.5. Multi-appointment scheduling in hospitals (MASPH). Unlike HHC, MASPH is gaining momentum in the academic literature, as observed in the review by Marynissen and Demeulemeester (2019). MASPH problems address a patient's need to sequentially visit multiple resource types in a hospital setting to receive treatment or diagnosis, for example, cancer treatments. Because MASPH is only just gaining momentum, it is currently only found in a limited number of hospital departments that have systems that directly address this. Several hospital resources are considered in MASPH including, doctors, specialists, beds, medical devices, diagnostic resources, chemotherapy chairs, and linear accelerators (used for radiotherapy). By extension, hospital departments included are rehabilitation (Braaksma et al., 2014; Kortbeek et al., 2017), diagnostic facilities (Azadeh et al., 2015, 2014), oncology (Leeftink et al., 2019; Suss et al., 2018), and operating rooms (Burdett & Kozan, 2016; Kazemian et al., 2017). From a patient's perspective, services that are considered for scheduling are either diagnostic or treatment. Furthermore, three types of patients are identified: outpatient, inpatient and emergency patients. In outpatient procedure planning, the main challenges are uncertain service times and patient no-shows (Tsai & Teng, 2014). For inpatient planning, most work has focused on minimising the length of stay (Conforti et al., 2011). For emergency patients, although their arrival is unforeseen, studies have focused on scheduling diagnostic laboratories tied to the emergency department (Azadeh et al., 2014). Studies also address the scheduling of different treatment steps in a treatment path of a triaged emergency patient following the assignment of a treatment path (Luscombe & Kozan, 2016). In contrast to other application areas where exact methodologies are popular for solving models, because of the complexity, most models are solved using metaheuristics (Azadeh et al., 2015) and multi-agent models (Kanaga & Valarmathi, 2012).

2.3.2. Supply chain management

Supply chain management in healthcare refers to the information, supplies and finances involved with the acquisition and movement of goods, and services from the point of supply to the end-user, to enhance clinical outcomes while controlling costs (Dobrzykowski et al., 2014; De Vries & Huijsman, 2011). These processes might relate to physical goods like drugs, pharmaceuticals, medical devices, health aids, and patients' flow (Beier, 1995). In this section, we examine reviews relative to a specific component of SCM, logistics. Furthermore, activities associated with logistics, such as facility location and inventory management, are inspected.

2.3.2.1. Logistics. It is defined as the process of planning, implementing, and controlling procedures for the efficient and effective transportation and storage of goods including services, and related information from the point of origin to the point of consumption based on customer requirements (Cordeau et al., 2006). This definition includes inbound, outbound, internal, and external movements. This section reviews literature articles on Home Health Care logistics (Gutiérrez & Vidal, 2013) and material logistics in hospitals (Volland et al., 2017).

Home health care logistics literature includes decision support across three contexts. These include 1. "design and planning decisions": dealing with issues of facility location and districting (Blais et al., 2003); 2. "resource planning and allocation": relative to issues of staff and inventory management (Chahed et al., 2009; Kommer, 2002), and 3. "service scheduling": concerned with staff routing and scheduling (Bredström & Rönnqvist, 2008). Gutiérrez and Vidal (2013) note that although most models support staff routing and scheduling decisions, a significant impact on system performance has not been observed. Therefore, a call for diversification of future research in strategic and tactical levels has been issued.

Volland et al. (2017) review literature on activities associated with handling physical goods in hospitals. These physical goods are related to the care of patients, including items such as pharmaceuticals, medical consumables, food, laundry, sterile items, laboratory samples, waste etc. The review categorised publications into four research topics, of which three employ optimisation models. (1) "Supply & procurement": relative to purchasing (Rego, Claro, & de Sousa, 2014), and aspects of the interface between drug manufacturers and wholesalers (X. Li et al., 2011). (2) "Inventory Management": includes literature on inventory policy (Rosales et al., 2014). (3) "Distribution and Scheduling": distribution within (Lapierre & Ruiz, 2007) and outside a hospital (Medaglia et al., 2009), and handling of sterile devices (Ozturk et al., 2014). A significant rise in the application of optimisation techniques has been observed. Wherein most Optimisation techniques are applied in streams (2) and (3). Optimisation in inventory management has primarily sought to minimise costs. Specifically, heuristics are applied to minimise the total, ordering, and inventory costs (Baboli, Fondrevelle, Tavakkoli-Moghaddam, & Mehrabi, 2011; Kelle. While in "Distribution and Scheduling", some models have sought to minimise costs associated with transportation, the number of routes, and travel mileage (Augusto & Xie, 2009; Medaglia et al., 2009; Shih & Chang, 2001).

2.3.2.2. Facility location. In its own right, this is an established topic of research within Operations Research. In healthcare, facility location problems concentrate on three main areas. These include healthcare facility location (involving community health clinics, primary care or specialist clinics, public and private hospitals), ambulance location and, hospital layout planning (Güneş et al., 2015). In essence, facility location problems locate a set of facilities (resources) to minimise/maximise specific objectives while fulfiling a set of demands concerning some constraints (Laporte et al., 2019). Objectives most commonly applied in healthcare facility location are: 1) minimise access cost for healthcare consumers, 2) maximise population with access to a healthcare facility, and 3) maximise the equity in access (Güneş et al., 2015). Increasingly, facility location has been proposed within the context of logistics as a sub-activity in several healthcare settings. These settings, along with their respective review papers, are supply chain (Dobrzykowski et al., 2014; De Vries & Huijsman, 2011), pharmaceutical supply chain (Lemmens et al., 2016; Narayana et al., 2012; Shah, 2004), healthcare waste management (Thakur & Ramesh, 2015) and emergency response (Daskin & Dean, 2004; X. Li et al., 2011).

We surveyed two reviews on the emergency and non-emergency facilities location (Ahmadi-Javid, Seyedi, et al., 2017; X. Li et al., 2011). X. Li et al. (2011) conclude that heuristics (Jia et al., 2007), simulation, and exact algorithms (Alsalloum & Rand, 2006) have been used to solve models that emphasised providing coverage for emergency calls. They also found that simulation has been used to either evaluate the performance of policies derived from the solutions of optimisation models (Maxwell et al., 2009) or in conjunction with heuristics to provide better quality solutions (Slocum et al., 2021). Through their analysis, Ahmadi-Javid, Seyedi et al. (2017) observe that cost minimisation is a major objective used in location problems (Ghaderi & Jabalameli, 2013; Mestre et al., 2015), and the minimisation of distance (or time) is considered a key factor in enhancing efficiency and effectiveness of locations (Beheshtifar & Alimoahmmadi, 2015; Smith et al., 2013). Furthermore, a large number of models are built using Integer Linear Programming (ILP) and Mixed-Integer Linear Programming (MILP) (Ares et al., 2016; Beheshtifar & Alimoahmmadi, 2015; Mestre et al., 2015), as opposed to stochastic programming (Mitropoulos et al., 2013) or dynamic programming (Elalouf et al., 2015).

2.3.2.3. Inventory management. This is another sub-activity of logistics management in supply chain management, with a focus on end-customer demand. Here, the aim is to improve customer service while lowering relevant costs (Cordeau et al., 2006). In the context of Healthcare, inventory management refers to the management and control of a large number and variety of stocked items. When needed, not having the supplies in-stock can seriously impact the quality of care (Moons et al., 2019), with consequences such as loss of life (Guerrero et al., 2013).

We survey two reviews. One, on inventory systems across various inventory items such as pharmaceuticals, medical equipment, surgical instruments, and other medical and surgical supplies (Saha & Ray, 2019). Two, inventory management of surgical supplies and sterile instruments (Ahmadi et al., 2019). Saha and Ray (2019) find that heuristics solve inventory problems under uncertainties (Rosales, Magazine, & Rao, 2015) and solve inventory allocation problems for surgical supplies stored in multiple locations. Through their analysis, Ahmadi et al. (2019) observe that early studies examined classical inventory models that relied on simplified assumptions, leading to far from practical solutions (Burns et al., 2001; Machline, 2008). On the other hand, research incorporating stochastic models did not specify which sources of uncertainty they considered (Little & Coughlan, 2008; Rappold et al., 2011). The review also demonstrated several strategies towards cost reduction and standardising practices utilised by practitioners (Eiferman et al., 2015; Park & Dickerson, 2009).

2.4. Mental healthcare

In this section, the distinctive features of mental healthcare are elaborated. In particular, we examine the nature of service models in mental healthcare, the causes and diagnosis of mental illnesses and their impacts on services, risks associated with mental illness and their consequences on service delivery, and finally, the integrated nature of psychological and physical health.

2.4.1. Care setting

The care of patients with mental illness has been subject to significant changes in the West over the last two centuries. In particular, from the 1960s onwards, many countries implemented the policy of deinstitutionalisation, which led to the movement of patients from large inpatient institutions into the community by establishing community services (Fakhoury & Priebe, 2007). Presently, it is widely recognised that effective mental healthcare services cannot be delivered exclusively within a hospital setting or exclusively within the community (Abdulmalik & Thornicroft, 2016). An optimal mix of hospital and community services is recommended (Thornicroft & Tansella, 2013). Yet, such a mix has only been achieved in a few high-income countries, where the relatively high availability of workforce and financial resources have been matched by political willingness to increase community care (Saxena et al., 2007). A diverse collection of service delivery models are currently in use in both low-middle-income countries and high-income countries (Carter, 2019; Cohen et al., 2011).

Mental health care relies on its human resources rather than advanced technology or equipment. The mental health workforce is a mix of collaboration between psychosocial providers and biomedical providers wherein the workforce is generally composed of three groups of individuals (Gask, 2005; Kakuma et al., 2011). The first includes specialist workers, such as psychiatrists, neurologists, psychiatric nurses, psychologists, mental health social workers, and occupational therapists (Kakuma et al., 2011). The second group is composed of non-specialist health workers, such as general practitioners/doctors, nurses, lay health workers, and caregivers (Gupta et al., 2019). The final group is formed of other professionals such as community-level resources that include formally structured bodies such as international and indigenous non-governmental organisations (NGOs) (Patel & Thara, 2003). The heterogeneity of service models across the world is no doubt challenging to the modelling of such services.

2.4.2. Uncertainty

Unlike the rest of medicine, a psychiatric diagnosis does not have any specific identifiable biological or psychological markers (Timimi, 2014). This is reflected through the diagnoses listed on major psychiatric diagnosis manuals such as Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) (American Psychiatric Association, 2013) and International Classification of Diseases (ICD-10) (World Health Organization, 1994). Unlike the rest of medicine, where the cause of a symptom is clarified by diagnosis, the cause of various mental disorders does not share the same scientific security (Clark et al., 2017). The heterogeneous use of diagnostic manuals further complicates this, wherein DSM-5 is primarily used in the United States, and ICD-10 is used internationally. The widely used diagnostic manuals have been subject to various criticisms, particularly for being fundamentally descriptive systems, based primarily on self-reported symptoms and observed signs (Clark et al., 2017).

The two widely used systems of diagnosis are increasingly bringing into question issues of clinical validity, reliability, impact on treatment and outcomes, and the uniformity of prognoses. Many psychiatrists have called for a shift from the current paradigm of a mental health diagnosis that focuses on the biomedical cause of mental disorders because of evidence-based research (Bracken et al., 2012). Research on the causes of mental illness has shown that it arises from several factors, including biological, behavioural, psychosocial, and cultural factors that interact in complex ways (Canino & Alegría, 2008). Research has also highlighted that, unlike the rest of medicine, outcomes of mental illnesses are not definable but are complex and variable combinations of psychological problems (Clark et al., 2017). With diagnoses of psychological disorders often overlapping and criteria frequently changing, the uncertainty created by these factors is a particular concern in mental healthcare (American Psychiatric Association, 2013).

2.5.1. Risks

Research has linked service availability and quality of care to patient safety (Brickell & McLean, 2011). Although a lack of awareness on the issue of patient safety has been highlighted, researchers have identified many risk factors for patient safety in mental healthcare (Callaly et al., 2005). Several patient risk factors from acute medical care settings apply to mental healthcare and are frequently adopted. However, safety issues exist that are unique to mental healthcare. Studies have identified medical errors to be the foremost risk to patients in hospitals for physical disorders. While in mental health, the main concern is self-destructive behaviour (suicide and attempted suicide), violence and self-harm (Brickell & McLean, 2011; Flewett, 2010). Furthermore, critical differences in risks between physical and mental healthcare are the prevalence of patients who do not believe they are ill and refuse treatment; staff safety is directly related to the specific manifestations of mental illnesses (Briner & Manser, 2013).

2.4.3. Physical and mental health

Although mental and physical illnesses have fundamental differences, as described above, they have been found to influence each other in several ways. Lifestyle changes in the modern population are said to contribute to poor physical health, affecting the incidence rates for mental illness (Hidaka, 2012). Research into the cross-effects between physical and psychological health has a strong link (Ohrnberger et al., 2017). Studies have also found in-direct pathways through which mental health affects physical health and vice versa (Ohrnberger et al., 2017). Several reviews and studies have highlighted that for people with severe mental illness, including schizophrenia and bipolar disorder, there are higher morbidity and mortality rates of cardiovascular diseases than the general population (De Hert et al., 2011). They also have high rates of infectious diseases, diabetes, respiratory disease, some forms of cancers and HIV (Cournos et al., 2005). On the other end of the spectrum, a similar trend can be observed. Here, for patients with physical disorders, particularly those with severe disorders such as stroke, cancer, and acute coronary syndrome, depression is prevalent and harms the course of these diseases. This information is integral to understanding the differences between physical and mental health and highlighting the connections and influence of one on the other as it shapes the service provision to tackle these complex and debilitating associations. There is much "physical" in "mental" disorders and much "mental" in "physical" disorders (Kendell, 2001).

An acknowledgement of links described above has resulted in the re-conceptualisation of care delivery into models of integrated care that involve co-location and interdisciplinary working of various health professionals, from mental health, physical health and social care (Hetrick et al., 2017). Although this integration improves outcomes, there are problems of sharing responsibility, uncertainties regarding the boundary between services and roles (Pomare et al., 2018).

2.5. Summary

This section demonstrates how optimisation methodologies have a diverse history of application in healthcare. The application of optimisation methodologies has evolved to accommodate and address the ever-changing and often shifting contextual priorities of healthcare services. We have also examined the distinctive characteristics of mental healthcare and associated services.

The optimisation literature appears to have examined characteristics similar to mental health services compared to other healthcare settings, as discussed in Section 2.2. However, a comprehensive account reviewing the optimisation literature in the context of mental healthcare services does not exist. With mental healthcare being one of the immediate healthcare priorities, the application of optimisation methodologies can address major obstacles of imbalances and inefficiencies often associated with mental healthcare services. Therefore, intending to identify the application of optimisation to mental healthcare services thus far, we conduct a literature review to define future research opportunities for the application of optimisation methodologies.

3. Method of review

A literature search was conducted on Scopus and Web of Science for papers published any time before December 2020, with a particular focus on articles that applied optimisation methodologies to mental healthcare service delivery. Table 2 contains a sample search strategy used across search engines and depicts the search results for each query. Additionally, a backwards referencing search and manual search of reference lists were conducted from the relevant articles, which yielded results. Additionally, Table A1 and Table A2 in the appendix provide further details on search terms that were used.

The identified articles underwent a set of rigorous screenings, based on two key inclusion criteria's: 1. an optimisation methodology is used; 2. the problem addressed has a mental healthcare service delivery focus. A similar inclusion criterion has been previously employed by Bradley et al. (2017). Moreover, only papers published in peer-reviewed journals and full papers in conference proceedings were included. Articles with a primary focus on epidemiology, prevention, screening, alcohol and substance abuse, and smoking cessation were not included. Following two screenings, a total number of 13 articles are included in the review, as depicted in Figure 1. Of the 13 articles published between 1976 and 2020, 7 were published before the 2000s and six after. Geographically, the majority of all articles were based on research conducted in the USA, followed by the UK.

Table 2. Sample Search Queries.

Web of Science	(ALL = ("heuristic" OR "metaheuristic") AND ALL = ("mental health*" OR "community mental health*" OR "psychi*") AND ALL = ("service*" OR "planning" OR "allocation" OR "scheduling" OR "design"))	22
	(ALL = ("optimization" OR "optimisation") AND ALL = ("mental health*" OR "community mental health*" OR "psychi*") AND ALL = ("service*" OR "planning" OR "allocation" OR "scheduling" OR "design"))	40
	(ALL = ("programming" OR "non-linear programming" OR "nonlinear programming" OR "linear programming") AND ALL = ("mental health*" OR "community mental health*" OR "psychi*") AND ALL = ("service*" OR "planning" OR "allocation" OR "scheduling" OR "design"))	153
	(ALL = ("mathematical model*" OR "mathematical program*") AND ALL = ("mental health*" OR "community mental health*" OR "psychi*") AND ALL = ("service*" OR "planning" OR "allocation" OR "scheduling" OR "design"))	11

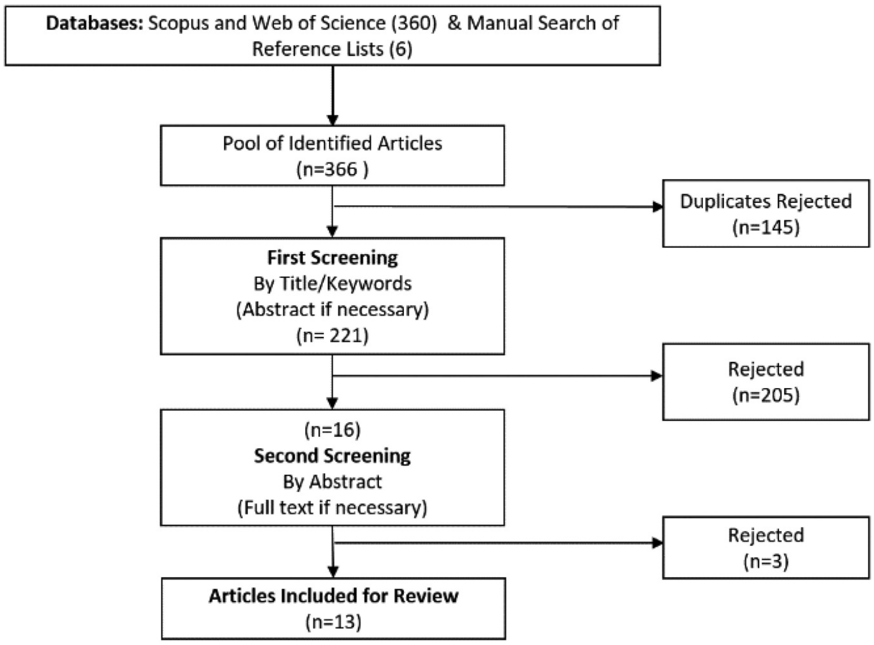

Figure 1. Search Strategy.

4. Analysis

To analyse and classify the literature under review, taxonomies employed by existing literature reviews were referenced. Specifically, reviews on the application of OR methodologies to a specific healthcare context such as home care and those addressing a particular problem such as scheduling were drawn upon. Consequently, we first describe a general overview of the literature, followed by an in-depth analysis of the optimisation models. Themes such as the level of planning, the type of planning decision, and the care setting where the study was conducted are described in this section and summarised in Table 3.

Table 3. Optimisation in Mental Healthcare Literature Thematic Overview.

Author	Planning Level	Planning Decision	Care Setting
Lyons and Young (1976)	Strategic	Capacity Dimensioning • Staff	Multi-care units
Wolpert and Wolpert (1976)	Tactical	Admission Control	Multi-site care network
Muraco et al. (1977)	Strategic	Regional Coverage • Care Centre Location	Multi-site care network
Heiner et al. (1981)	Tactical	Admission Control	Multi-site care network
Franz et al. (1984)	Strategic	Placement Policy	Multi-site care network
Leff et al. (1986)	Tactical	Admission Control	Multi-site care network
Specht (1993)	Strategic	Placement Policy	Multi-site care network
Bester et al. (2007)	Operational (Offline)	Staff-to-Shift Assignment	Multi-care units
Cohn et al. (2009)	Tactical	Staff-Shift Schedule	Multi-site care network
Hertz and Lahrichi (2009)	Tactical Operational (Offline)	Admission Control Assessment and Intake Visit Scheduling • Short-Term Care Plan • Staff-to-Visit Assignment	Multi-site care network
Pagel et al. (2012)	Tactical	Appointment Scheduling	Multi-site care network
Samorani and LaGanga (2015)	Tactical	Appointment Scheduling	Single-care unit
Y. Li et al. (2016)	Operational (Offline)	Patient-to-Appointment Location Scheduling Visit Scheduling • Staff-to-Visit Assignment	Multi-site care network

4.1. Planning level & planning decisions

Seven studies were conducted before the 2000s. Specifically, the deinstitutionalisation of mental healthcare services- a dramatic movement of patients from state mental hospitals to the community- that began in the 1960s steered the development of optimisation models to provide transitional support. Four studies address planning decisions on a strategic level, and three address tactical level planning decisions (See Table 3). As for the classification of articles post-2000s, six are identified, three of which address decisions on a tactical planning level, two on an offline operational level, and one on both tactical and offline operational level. Notably, studies addressing strategic level decisions are absent in recent mental healthcare literature. A similar trend is observed in healthcare, where operational level planning has received the most attention. Researchers have called for more diversification in strategic and tactical planning. In contrast, online operational level planning has not been investigated in the existing mental healthcare literature. Overall, the sporadic distribution of articles and the restricted number of publications on research in mental healthcare service planning and delivery as opposed to physical healthcare are telltale signs of the limited attention given to this aspect of healthcare.

The classification of planning decisions is based on the taxonomic classification described in a review by Hulshof et al. (2012). We identify a variety of decisions across three planning levels. First, studies have tackled decisions on placement policy, regional coverage, and capacity dimensioning on a strategic level. Placement policy decisions aim to establish types of patients to the right treatment at an appropriate time through cost-effective means. Herein patients are classified based on their diagnosis, care required, and the location where care can be dispensed. These early optimisation models enabled mental health planners to simultaneously evaluate several uncertain parameters resulting from changing government fiscal policies and the availability of funds. In particular, optimisation models were used to analyse several policies to fulfil what was termed the "goal of deinstitutionalisation" of reassigning noncritical patients to nonresidential services while meeting demand using available resources (Franz et al., 1984; Specht, 1993). Regional coverage involves decisions on the number, type, and location of care facilities. In our review, under conditions of centralised geographic demand, client accessibility and convenience strategies are assessed. In particular, Muraco et al. (1977) demonstrated that the deconcentrating of mental health services under conditions of centralised demand resulted in pseudo concentration that masked the actual concentration in the service delivery system. Capacity dimensioning involves the testing of alternative scenarios for staff size or availability to fulfil projected demand. Lyons and Young (1976) described a model for allocating staff within a large psychiatric hospital. The model formulation incorporated a patient needs survey for various therapeutic activities and activity analysis of staff functions.

Several planning decisions have not been addressed on a strategic planning level in mental healthcare compared to healthcare. For instance, we found no evidence of studies addressing the "Facility Layout" and "Care Unit Partitioning" decision. The facility layout concerns the positioning and organisation of various physical areas in a facility. The decision related to dividing an inpatient facility into care units is called care unit partitioning decisions. These decisions are critical elements of in-care mental health safety and harm reduction. In particular, designing facilities with increased visibility to allow staff to monitor and observe at-risk patients closely has the potential to help minimise the risk of suicides (Reiling et al., 2008).

Additionally, "case mix" which is the volume and composition of patient groups that the facility serves; "panel size", the number of potential patients; and "service mix", the particular services a facility provides, are all decisions that are yet to be addressed in mental healthcare literature. These decisions on a strategic level aim to help maintain a minimum standard of service while efficiently using scarce resources. Mental healthcare services could greatly benefit from deploying optimisation models to address these decisions, especially given the issues of accessibility and reduced resource availability.

Second, on a tactical level, admission control decisions, appointment scheduling, and staff-shift schedule have been addressed. Admission control relates to determining rules on which a patient can be admitted from a waiting list into a service. Hertz and Lahrichi (2009) proposed a model that balances nurses' workload who provided long-term and short-term care to five categories of patients, including patients with serious mental health problems. At the same time, several studies developed models that allocated resources and various treatment modalities to patients categorised based on their needs and diagnosis. In particular, Heiner et al. (1981) developed a resource allocation and evaluation model for several clusters of intellectually disabled patients in a multi-service delivery system based on efficiency, effectiveness, and equity measures. Leff et al. (1986) developed a planning model that allocated services to chronically mentally ill patients to improve care outcomes. Appointment scheduling has involved the development of a blueprint used to specify a time and date for patient consultation/treatment. Samorani and LaGanga (2015) set out to overbook appointments optimally given no-show predictions of patients in a large mental health centre with a high no-show rate. Pagel et al. (2012) allocate appointments subject to waiting times to maximise desired clinical outcomes in a primary mental healthcare system. Scheduling of shifts to staff determines which shifts are to be worked and by how many employees. A shift-staff schedule is developed for medical residents specialising in psychiatry at a medical university, spanning 365 days by Cohn et al. (2009).

We could not find studies that addressed several tactical level decisions such as capacity allocation, patient routing, and unused capacity (re)allocation that are available in healthcare literature. Particularly relevant planning mental healthcare services are capacity allocation decisions where resource capacities settled on the strategic level are subdivided over patient groups. For many countries, increasing mental healthcare provision and ensuring that resources are distributed equitably are priorities (Anselmi et al., 2020). Increasingly, the geographical distribution of resources is encouraged to reflect need. As such, an optimisation model for capacity allocation can be a means to achieve equitable distribution of access.

Lastly, operational decisions on staff-to-shift assignment, assessment and intake, visit scheduling, and patient-to-appointment location scheduling are addressed. Based on the staff-shift schedule, specific dates and times associated with shifts are assigned to staff in staff-to-shift assignments. For instance, Bester et al. (2007) use their model to build duty rosters for nurses at a psychiatric facility that includes a fairness component. Assessment and intake decisions include a process wherein a patient referred to a service is assessed for eligibility (based on the placement policy), care requirements are determined, and a care provider is assigned. Such a model was built by Hertz and Lahrichi (2009) to assign a care provider with a workload-balancing component. Similar to staff-shift scheduling, visit scheduling involves determining which staff member will perform a visit on which day and time. Visit scheduling was modelled for travelling physicians (Y. Li et al., 2016 and home care workers (Hertz & Lahrichi, 2009). Based on the appointment schedule blueprint developed on a tactical level, the scheduling of a particular patient to a specific location has been addressed in the literature. Specifically, to improve access to care, Y. Li et al. (2016) investigated the problem of scheduling patients with chronic mental disorders to an outreach clinic location.

Some operational planning decisions that have not been considered in mental healthcare are decisions associated with short-term care planning, as observed in the context of home care services (Hertz & Lahrichi, 2009). Another set of planning decisions that have not been modelled in mental healthcare is scheduling a combination of appointments as observed in cancer care (Petrovic et al., 2011) and a series of appointments modelled in rehabilitation care (Chien et al., 2008). In particular, individuals with severe complex mental health needs often require support from several different agencies in the community. Internationally, "case management" policies have been devised to promote patient-centred care coordination and care planning for individuals with complex health needs combining multiple chronic conditions with psychosocial or mental health comorbidities (Hudon et al., 2017). Broadly speaking, case management is an umbrella term for various care models that ensure that service users are provided with coordinated, effective and efficient care based on an assessment of their needs. In mental healthcare, such a care model is concerned with comprehensively coordinating services to meet a patient's mental health needs. Variants are found in the USA (Rapp & Wintersteen, 1989), the UK (Department of Health, 1990), Australia (Rickwood, 2006), New Zealand (Mental Health Commission, 2012), and the Netherlands (Van Veldhuizen, 2007). Although policy aspirations have created an expanded mental health system that encompasses large-scale care provision to people living in the community, a significant gap exists between policy aspirations and operational practices (Jones et al., 2018). Services face challenges in designing operations that support staff and service users in realising personalised care. As discussed in section 2.3.1, MASPH is only just gaining momentum in the hospital settings to address a patient's need to access multiple resources. In contrast, models for settings outside the hospital are still missing. In particular, the gap does extend to care provided in the community and to mental healthcare.

In this section, we have established that optimisation models in mental healthcare have focused mainly on the application area of planning, scheduling and routing. In Section 2.3, we have demonstrated that a good proportion of healthcare optimisation literature has also focused on this area. We have found several parallel and gaps in the levels of planning and decision types between the two contexts in this area. However, we found no evidence of models for the supply chain management of mental healthcare. Notably, inventory management does not apply to mental healthcare, as it does not involve the use of medical instruments. However, facility location as an area of research is highly relevant to mental healthcare as it is to extant healthcare. Among the challenges associated with reduced access or discontinuity of care in mental healthcare services is the geographical distance to services (Carbonell et al., 2020). Existing optimisation models for healthcare facility location have been deployed to minimise access costs for healthcare consumers, maximise population with access to a healthcare facility, and maximise the equity in access (Güneş et al., 2015). This extensively researched area of application is unexplored in mental healthcare and is a promising avenue for future research.

4.2. Care Setting

Articles are classified into three care settings based on the number and distribution of care units that were the focus of modelling: single care unit, multi-care unit, and multi-site care network. A single care unit refers to one health centre, for instance, a single outpatient clinic, as observed in the study by Samorani and LaGanga (2015). On the other hand, multi-care units refer to a single care organisation with multiple subunits, for instance, a psychiatric hospital with several wards, as seen in studies conducted by Lyons and Young (1976) and Bester et al. (2007). Moreover, a multi-site care network comprises multiple care units distributed over a geographic area. Most articles under review have built models to address planning issues in such networks, such as a regional hierarchical care system (Muraco et al., 1977); a conceptual network of community mental healthcare system spanning across local, state and federal bodies (Wolpert & Wolpert, 1976); a system composed of numerous distinct mental healthcare providers (Heiner et al., 1981; Leff et al., 1986); and a care system consisting of a hospital and community mental health care centre (Franz et al., 1984; Specht, 1993). More recently, models have been used to address planning issues in a network of multiple sites such as psychiatric hospitals (Cohn et al., 2009; Pagel et al., 2012); home care services (Hertz & Lahrichi, 2009); and outpatient speciality clinics (Y. Li et al., 2016). Remarkably, models in mental healthcare literature are spread over a range of care settings, reflective of the diversity inherent in the services. In contrast, modelling multiple care settings is a relatively recent development in other healthcare services.

4.3. Model Objectives

This section describes objective functions used in optimisation models in planning mental healthcare services so far. Optimisation models can have single or multiple objective functions. In a single objective function model, the optimal decision is taken based on one objective. In a multi-objective function model, more than one objective must be satisfied (Hwang & Masud, 2012). Our analysis has found that 5 of the 13 papers have used multi-objective function models, as seen in Table 4. Furthermore, the objective functions are divided into five observed categories: maximisation of patient outcomes, maximisation of constraint/goal satisfaction, minimisation of costs, maximisation of resource allocation and utilisation, and minimisation of patient dissatisfaction. Table 4 depicts the objective functions for each article.

4.3.1. Maximising Constraint/Goal Satisfaction

As described by the Donabedian framework, quality of care includes the organisation of care (or structure), the influence of structure on care delivery processes, and patient-level health care outcomes (Kilbourne et al., 2018; McDonald et al., 2007). Therefore, to provide safe, effective, patient-centred, timely, efficient, and equitable care, services are faced with diverse priorities and competing goals. 4 of the 13 papers under review define multiple goals in their objective. Specifically, Franz et al. (1984) and Specht (1993) explore multi-objective optimisation using goal programming for resource allocation. Both models maximise and prioritise diverse, conflicting goals, including budget, patient load, patient admission/reassignment, community education, demand satisfaction, staff and service capacity. More recently, Cohn et al. (2009) found the most feasible schedule that satisfies constraints of staff availability, staff capacity, staff preference, and demand satisfaction while also emphasising schedule fairness. Similarly, Hertz

Table 4. Classification of Literature Based on Objective Functions.

	Max. Objectives			Min. Objectives		
Authors	Resource Allocation & Utilisation	Constraint Satisfaction	Patient Outcomes	Costs	Patient Rejection/ dissatisfaction	Patient Travel Time
Lyons and Young (1976)	✓					
Wolpert and Wolpert (1976)			✓			
Muraco et al. (1977)				✓		
Heiner et al. (1981)	✓		✓			
Franz et al. (1984)		✓				
Leff et al. (1986)			✓			
Specht (1993)		✓				
Bester et al. (2007)				✓		
Cohn et al. (2009)		✓				
Hertz and Lahrichi (2009)		✓				
Pagel et al. (2012)			✓			
Samorani and LaGanga (2015)				✓		
Y. Li et al. (2016)					✓	✓
	2	4	4	3	1	1

and Lahrichi (2009) model fairness as a function of workload balancing, measured by minimising travel load, caseload and visit load of staff.

4.3.2. Maximising patient outcomes

In mental healthcare, patient outcomes measure whether the care received by a patient has led to improvements in their symptoms – e.g., improvement or remission – or functioning or treatment completion (Kilbourne et al., 2018). These measures assist service providers in planning, monitoring and adjusting treatment options. Similar outcomes have been modelled as objective functions of 4 articles. Leff et al. (1986) define an objective function in which patient outcome is the maximisation of the net forward movement of a patient in a care system in terms of functional improvement or regression. Along similar lines, Heiner et al. (1981) define an objective function that maximises the aggregate improvement in the functioning of each patient cluster (also called the deinstitutionalisation objective). Wolpert and Wolpert (1976) define an objective function that maximises outcomes by reducing patient dependency on mental healthcare, social welfare and law enforcement. More recently, maximising the number of patients who complete treatment was considered as the objective in the model built by Pagel et al. (2012).

4.3.3. Minimising costs

Whilst mental illness accounts for 13% of health care costs globally, it receives on average 3% of healthcare funding in mid, high-income countries and 0.5% in low-income countries (World Health Assembly, 2012). When mental health issues are recognised and responded to, they have sizeable impacts on budgets associated with treatments delivered in inpatient, outpatient, community and primary care settings (Knapp & Lemmi, 2019). Consequently, economic costs associated with mental disorders and disease are generally distinguished between direct and indirect costs (Trautmann et al., 2016). Direct costs – also referred to as "visible costs" – are associated with diagnosis and treatment in the healthcare system, including the use of hospital services, medication, staff time, ambulances, psychotherapy, and primary and community care (Ride et al., 2019). Indirect costs – also called "invisible costs" – include reduced labour supply, premature mortality, reduced health-related quality of life, lost output, lost tax revenue, transfer payments, and unpaid care by family or friends (Emily & Valerie, 2014). Costs associated with treatment in the mental healthcare system have been used in 3 of 13 papers we review. Specifically, Muraco et al. (1977) define a single objective function that minimises costs incurred by a client when travelling to treatment centre locations. Bester et al. (2007) describe a multi-objective function, which is a combination of remuneration costs and accumulated nurse dissatisfaction – a measure of mismatch between their schedule preference – corresponding to current and previous assignments. More recently, Samorani and LaGanga (2015) maximised the profits of a mental healthcare centre by overbooking appointments on a schedule. Herein, profits are maximised to minimise costs associated with patient waiting time and clinic overtime, besides also maximising the number of patients seen.

4.3.4. Maximise resource allocation & utilisation

Many countries face the challenge of providing adequate human, material, technological, and financial resources for delivering essential mental health services. Lack of funding – described in minimising costs – is compounded with a worldwide shortage of human resources for mental health (World Health Organization, 2018b). Therefore, mental healthcare services often consider allocating and utilising their human resources with *outcome* vs *output and productivity* (Daniels, 2016; Davies, 2006). Specifically, a fundamental trade-off is between meeting patient needs (medical outcome) and contractual agreements (outputs) in allocating staff. Of the papers under review, Heiner et al. (1981) define an objective function that minimises deviation from improvement in patient outcome by ensuring equitable distribution of resources (staff and services). Besides, efficient utilisation of resources is about maximising productivity by matching staff to appropriate roles by considering skill mix, role design, staff shortages and inequities, and service requirements. Lyons and Young (1976) modelled an objective function that maximises staff utilisation by maximising an aggregate appropriateness score for all personnel performing activities. Herein, appropriateness levels for 12 types of personnel for the performance of 13 planned therapeutic activities in the service were fed to the model.

4.3.5. Minimise Patient Rejection/Dissatisfaction

A recent study allocates optimal appointment locations for patients and includes the minimisation of the penalty associated with unsatisfied appointment requests, in addition to minimising the travel time for patients (Y. Li et al., 2016).

4.4. Model constraints

Constraints are generally interpreted as limits or boundaries governing the system being modelled. The nature of these limits is diverse and includes limits on the availability of resources, funding, time-based limits (temporal) and capacity. In this review, constraints have been grouped based on their primary focus and the nature of their application. Specifically, constraints have focused on the service provider, staff and patient, and the nature of the constraints are relative to service delivery, geography and temporality. Table 5 provides a detailed overview of the constraints with respect to their publication.

4.4.1. Service delivery constraints

Service delivery constraints have been considered in relation to the service provider and service staff. Constraints used in models are relative to budget, resource availability, service capacity, assignment of tasks to staff, assignment of service packages and mandatory services.

A recent study produced country-level estimates in the Americas for the proportion of total disease burden to the health expenditure and found a striking imbalance in the ratio between disease burden of mental health and allocated spending (Vigo et al., 2019). The spending ranged from 3:1 in Canada and the USA to 435:1 in Haiti, with a median of 32:1 across 30 countries (Vigo et al., 2019). Because of such historical imbalances, models in literature have given considerable attention to budgeting. Articles under review have examined the allocation of a fixed budget (Franz et al., 1984; Heiner et al., 1981; Leff et al., 1986; Lyons & Young, 1976; Specht, 1993; Wolpert & Wolpert, 1976). These articles have included a diversity of budgetary constraints in their models, such as the maximum allowable monetary expenditure (Franz et al., 1984; Specht, 1993; Wolpert & Wolpert, 1976), per capita budget (Leff et al., 1986), total available personnel budget (Lyons & Young, 1976); and government-mandated budget (Heiner et al., 1981).

Evidence indicates that mental health workers account for only 1% of the global health workforce. Approximately 45% of the global population resides in a country with less than one psychiatrist per 100,000 people (World Health Organization, 2018b). Two articles have defined limits on the availability of resources. Leff et al. (1986) set an upper limit on the amount of personnel available in the service, whereas (Lyons and Young (1976) have a fixed number of beds. Furthermore, mental health services continually experience rising demands and, in many cases, exceed available capacity. For instance, bed occupancy rates for inpatient services regularly exceeds recommended levels to maintain safety standards, highlighting the significant pressure the system is under (World Health Organization, 2018b). Therefore, a variety of service capacity constraints, such as the limitation on service provider capacity (Heiner et al., 1981), number of available service hours (Y. Li et al., 2016; Lyons & Young, 1976) and the maximum number of appointments (Pagel et al., 2012), have been formulated.

From a staffing perspective, constraints focusing on task assignment, staff preferences, the sequence of shifts and skill requirements have been considered. Assignment of tasks to the staff mainly specifies

Table 5. Classification of Literature Based on Model Constraints.

	Service Provider								Staff						Patient
	Delivery					Geographic		Temporal	Delivery				Geographic	Temporal	Temporal
Authors	Budget	Resource Availability	Service Capacity	Mandatory Service Requirements	Service Package Assignment	Demand Coverage	Patient Load Balancing	Lead Time	Staff Assignment Thresholds	Staff Preference	Shift Sequence	Skill Requirement	Location Preference	Worktime Thresholds	Patient Waiting Time
Lyons and Young (1976)	x	x	x											x	
Wolpert and Wolpert (1976)	x														
Muraco et al. (1977)						x	x								
Heiner et al. (1981)	x		x	x											
Franz et al. (1984)	x					x	x						x	x	
Leff et al. (1986)	x	x			x										
Specht (1993)	x			x		x	x							x	
Bester et al. (2007)									x		x	x			
Hertz and Lahrichi (2009)												x			
Pagel et al. (2012)			x	x											x
Cohn et al. (2009)				x						x			x	x	
Samorani and LaGanga (2015)					x			x						x	
Y. Li et al. (2016)			x						x				x		

permissible values of the maximum and the minimum number of staff per task or tasks per staff. Examples include constraints that specify the minimum and the maximum number of shift assignments for a nurse (Bester et al., 2007) and constraints limiting any physician's assignment to an outpatient appointment (Y. Li et al., 2016). Additionally, staff preference constraints have been used to model vacation and weekly shift assignment requirements in the appointment-scheduling problem (Cohn et al., 2009). Instances of constraints corresponding to skill requirements include defining the minimum number of nurses of a particular rank to be assigned to a shift (Bester et al., 2007) and assigning a patient to a type of nurse (Hertz & Lahrichi, 2009).

Several countries rely on government policies that specify values, principles and objectives of a population's mental health (Zhou et al., 2018). These policies are implanted in several domains such as service organising, service provision, service quality, human resources etc. (Zhou et al., 2018). Countries face several challenges in the implementation of these policies. Articles under review have modelled such features as constraints related to mandatory (government or service organisation) service hours for a service or groups of services. Heiner et al. (1981) formulate the mandated number of service hours for each individual in a patient cluster – based on functional skills, social skills and motor disabilities.

In contrast, Cohn et al. (2009) model the mandatory coverage for a network of hospitals as a constraint by specifying the compulsory presence of one primary and backup member of staff on any given day. A minimum limit on the number of three different types of appointments to be allocated is included by Pagel et al. (2012), and mandatory patient follow-up constraints are outlined by Specht (1993). Lastly, constraints ensuring appropriate service assignment to patients are defined in the resource allocation model built by Leff et al. (1986). A constraint ensures that patients at a functional level are assigned suitable service packages. Whereas, for booking outpatient appointments, a constraint allocates at most a single appointment slot to a patient (Samorani & LaGanga, 2015).

4.4.2. Temporal constraints

In this section, temporal constraints relative to service providers, staff and patients are examined. These constraints are based on time relationships between entities. Specifically, these are used to orient an event on a timeline, specify the duration of an event, and determine the order of an event to other events. There are two main types of temporal constraints, sequencing and real-time (Kuhn et al., 2015). Sequencing constraints specify the order in which a sequence of actions or events is allowed to take place. For instance, a sequential constraint would specify that two night shifts should not be scheduled in sequence. On the other hand, a real-time constraint may specify the explicit references to time. For instance, an event must take place 10 minutes before another event. From a service provider perspective, Samorani and LaGanga (2015) have included a lead-time (time between initiation and completion of process) constraint for booking appointment requests, which ensures that any request is assigned to at most one of the days that follow its arrival.

From a staff perspective, because of limited resource availability, staff are said to experience "brain drain" resulting in low morale and high turnover. This leads to a significant obstacle in retaining staff required to deliver services (Thornicroft et al., 2016). For instance, the National Health Service in the UK has recorded a drop of 11% in the mental healthcare nursing workforce between 2009 and 2019 (Buchan et al., 2019). Therefore, the prevention of overburdening workloads is a critical challenge in managing the workforce. In addition to addressing capacity issues described in the previous section, the distribution of tasks/work to staff is defined within a model through temporal constraints. Cohn et al. (2009) have included restrictions on the number of daily and weekly on-calls for staff. While studies published before the 2000s have formulated constraints that limit the number of hours staff spend supervising or receiving supervision (Lyons & Young, 1976) and constraints on total time available for psychiatrists to dispense services (Franz et al., 1984; Specht, 1993).

Finally, for a patient, shorter waiting times are said to affect patient outcomes positively. This is particularly so for conditions such as psychosis and in services for children and adolescents (Reichert & Jacobs, 2018; Schraeder & Reid, 2015). Waiting times have been observed to be a contributing factor to high rates of "no shows", greater likelihood of disengaging from services and worsening of conditions (Schraeder & Reid, 2015). By reducing waiting time, services have the potential for efficiency gains and cost savings. Furthermore, studies have found that rapid access reduces the "no show" rates falling by more than half and reduces crisis hospitalisations (Williams et al., 2008).

Additionally, from an economic point of view, poor outcomes related to an extended waiting period, which prevents patients from working, has associated costs (OECD, 2020; Reichert & Jacobs, 2018). While waiting time is often incorporated into the objective function, waiting times as temporal constraints have been included by Pagel et al. (2012) to facilitate introducing a new care systems model. These constraints specify the maximum allowable increase in waiting time for patients and define waiting-time periods for different service types.

4.4.3. Geographic constraints

Although mental health services do not adhere to a distinguished model of providing care, most services are in inpatient or community settings. While accessibility to services is impacted negatively by waiting lists, equally important is the uneven geographical distribution of service locations and staff (Samartzis & Talias, 2020). Geographic constraints in mental healthcare optimisation literature have primarily been associated with planning models built to aid deinstitutionalisation. Therefore, they have been applied to a large region consisting of a network of care services. Franz et al. (1984) and Specht (1993) have considered two types of constraints. The first type satisfies patient demand in a region and increases the number of patients reached by community-based educational programmes. Second increases the flow/transition of patients from institutional care to community care. A single article addresses facility location of community mental health services in a geographical area by incorporating demand coverage constraints to equally assign demand amongst community centres (Muraco et al., 1977). In contrast, staff-related geographical constraints have taken the form of location preferences. For instance, preferences are taken into consideration for determining appointment locations for medical residents (Cohn et al., 2009), community staff (Franz et al., 1984) and physicians (Y. Li et al., 2016).

4.5. Model formulation

Five types of optimisation techniques have been employed by the studies included in our review: linear, integer, mixed-integer, goal and stochastic programming. Linear programming is an optimisation technique to determine the value of decision variables that maximise or minimise a linear objective function where decision variables are subject to linear constraints (Chong & Zak, 2004; Vanderbei, 2020). Linear programming is employed in various application areas, including production planning, inventory control, and workforce planning (Mula et al., 2006; Taha, 2017). Of the articles under review, linear programming has been used for locating care centres (Muraco et al., 1977), assigning patients to services (Heiner et al., 1981; Leff et al., 1986; Wolpert & Wolpert, 1976), and scheduling appointments (Pagel et al., 2012). Furthermore, Integer programming is the same as linear programming except that all decision variables are constrained to be integers. When some but not all decisions are restricted to be integers, the optimisation technique is referred to as mixed-integer programming (Taha, 2017). Integer programming is often used to formulate scheduling problems (Vanderbei, 2020). In this review, scheduling of patient appointments (Y. Li et al., 2016) and staff (Bester et al., 2007; Cohn et al., 2009) have been modelled using integer programming. While staff dimensioning (Lyons & Young, 1976) and assigning patients to services are addressed using mixed-integer programming (Hertz & Lahrichi, 2009).

Goal programming can be thought of as an extension of linear programming to handle multiple, conflicting objectives. A target value to be achieved is specified for each goal, and unwanted deviations are then minimised (Winston & Goldberg, 2004). Often, goal programming is used to provide the best satisfying solution under conditions of multiple goal priorities. Among the 13 articles under review, two have used goal programming to analyse alternative placement policies (Franz et al., 1984; Specht, 1993). Stochastic programming constitutes a framework for modelling optimisation models in the presence of uncertainty (Ruszczynski & Shapiro, 2003). Decision problems addressed by stochastic programming are canonically expressed as “some decisions must be made today, but important information will not be available until after the decision is made” (King & Wallace, 2012). Samorani and LaGanga (2015) incorporate uncertainty regarding appointment cancellation and no-show probability by formulating a model using stochastic programming.

The optimisation techniques used to formulate problems in a mental healthcare setting are similar to techniques used in extant healthcare. However, as can be observed, optimisation in mental healthcare is limited and sporadically dispersed. Therefore, it appears that the choice of formulation technique is essentially a reflection of “when” the study was conducted and corresponds to the progressive development of optimisation techniques. Even so, the more recent study by Samorani and LaGanga (2015) is an exemplar in healthcare research for having been the first to integrate predictive analytics, optimisation and overbooking for scheduling.

4.6. Solution Algorithm

Once the model is defined, it can be solved by a solution algorithm. Formalised by Turing (1937) and Church (1936), an algorithm is a finite set of well-defined instructions for accomplishing a task. In optimisation, an algorithm’s goal is to find a solution with minimal or maximal evaluation time (Rothlauf, 2011).

Solution algorithms for optimisation problems can be roughly distinguished into two types: exact algorithms and heuristics. Articles under review have been categorised based on the type of solution algorithm deployed, as seen in Table 6. Most often, the solution algorithm of choice speaks to the complexity and size of a problem. This section will explore each model solution based on the type.

Table 6. Classification of Literature Based on Solution Algorithms.

Author	Model Formulation	Solution Type	Solution Algorithms	Solver
Lyons and Young (1976)	Mixed-Integer Programming	Exact	Branch and Bound	
Wolpert and Wolpert (1976)	Linear Programming		Simplex	
Heiner et al. (1981)	Linear Programming		Simplex	
Franz et al. (1984)	Goal programming		Simplex	IBM's MPSX
Leff et al. (1986)	Linear Programming		Nested Decomposition	
Specht (1993)	Goal programming		Simplex	
Cohn et al. (2009)	Integer Programming		Simplex	CPLEX
Pagel et al. (2012)	Linear Programming		Simplex	Microsoft Excel
Muraco et al. (1977)	Linear Programming	Heuristics	Alternating Heuristic	
Y. Li et al. (2016)	Integer Programming		Primal and Local Search Heuristics	CPLEX
Bester et al. (2007)	Integer Programming	Metaheuristics	Tabu Search	Microsoft Visual Basics
Hertz and Lahrichi (2009)	Mixed-Integer Programming	Exact & Metaheuristic	Branch and Cut & Tabu Search	CPLEX
Samorani and LaGanga (2015)	Stochastic programming	Exact and Heuristic	Column Generation & Heuristic	

4.6.1. Exact solution algorithms

Exact solution algorithms are designed in such a way that they guarantee finding an optimal solution in a finite amount of time. To do this, exact algorithms conduct an exhaustive search of every single solution in the solution space. Exact solutions algorithms were employed by 10 (of 13) articles under review. The most used algorithm was simplex ($n = 6$), whereas branch-and-bound, branch-and-cut, column generation and nested decomposition were used once by four different articles.

Wolpert and Wolpert (1976), Heiner et al. (1981) and Pagel et al. (2012) have solved their linear programming problem by directly applying the simplex algorithm. The simplex algorithm effectively solves Linear Programming (LP) problems with continuous decision variables (Dantzig, 1998). In particular, the algorithm finds an optimal solution to a problem, where the objective function depends linearly on the continuous decision variables. Specifically, the algorithm sequentially tests multiple values in a set of feasible values to improve the objective function until the optimal solution is found. Franz et al. (1984) and Specht (1993) used the goal programming variant of the simplex algorithm, which operates on multiple objective functions, where each objective is ranked. The algorithm prioritises goals with a higher priority, unlike in LP, where an objective function is optimised.

Lyons and Young (1976) employ the Branch and Bound (B&B) algorithm to solve a mixed-integer programming problem. B&B is a common enumerative approach to solving LP problems with discrete decision variables. Solving a problem using B&B involves recursively decomposing a problem into sub-problems, which are then solved using LP methods like the simplex algorithm (Land & Doig, 2010). Hertz and Lahrichi (2009) used Branch and Cut (B&C) to solve a mixed-integer programming problem. B&C algorithms combine B&B with cutting planes methods. Specifically, cutting plane methods add additional constraints (cutting planes) to a problem. The original constraints are replaced by alternative constraints closer to producing a feasible integral solution and exclude fractional solutions (Mitchell, 2000). Leff et al. (1986) deployed a nested decomposition algorithm (Glassey, 1973) to solve the resource allocation model. Decomposition algorithms split a problem into a master problem and one or more slave problems. The solution of the master problem is then fed to the slave problem to determine feasibility Dantzig & Wolfe, 1961).

Samorani and LaGanga (2015) used column generation to solve an integer programming problem. This approach is selected for scheduling outpatient appointments to keep the number of constraints low. A column generation algorithm is typically applied to problems where it is not possible to consider all variables explicitly (Desaulniers et al., 2006). Therefore, a problem is split into two problems: the restricted master problem and the sub-problem. The master problem works only with a sufficient subset of variables. In contrast, the sub-problem is created to identify new promising variables with reduced negative cost, which are then added to the master problem and resolved. This process is repeated until no negative reduced cost variables are identified.

4.6.2. Heuristics

For large problems, which cannot be solved using exact algorithms, heuristics are employed. Heuristics do not guarantee an optimal solution and generally return suboptimal solutions. Furthermore, heuristics are often problem-specific. In literature, two types of heuristics are distinguished: construction heuristics and improvement heuristics (Rothlauf, 2011). Construction heuristics build a complete solution from scratch by following a step-wise creation process. On the other hand, improvement heuristics start with a complete solution and then try to improve the solution iteratively. Three studies have utilised heuristics to solve their optimisation problems.

Samorani and LaGanga (2015) develop a new heuristics policy to schedule outpatient appointments. Since the "column generation" approach took a long time to solve – if the rejection of patients is not allowed – a new heuristic policy was developed and solved to near optimality. The heuristic schedule predicted shows in the near future and predicted no-shows into the future. This new procedure was found to outperform the exact solution. Further, Muraco et al. (1977) deployed an "alternating heuristic" represented by alternate steps of location assignment and demand allocation, which continues until an optimal minimal configuration is achieved within the given constraints. This heuristic was used to find a location with minimum transport and then assign a service centre to each location, followed by the allocation of demand to these centres.

Y. Li et al. (2016) employ both construction and improvement heuristics to construct physician assignments in an outpatient care network. Specifically, several column generation based primal heuristic algorithms were used to construct assignments, followed by several local search algorithms to improve the assignments further. In particular, heuristics that are based on exact methods are called primal heuristics (Joncour et al., 2010). In contrast, local search heuristics are applied to problems that are formulated to find a solution that maximises a criterion among several candidate solutions. Notably, the algorithm moves from solution to solution in the space of candidate solutions by applying local changes, until a time-bound elapses or an optimal solution is found.

4.6.3. Metaheuristic

Improvement heuristics that use a search strategy that is general, widely applicable and problem-invariant are denoted as metaheuristics (Glover & Kochenberger, 2006). Two of the articles under review have employed metaheuristics. Bester et al. (2007) developed a decision support tool for nurse rostering that is underpinned by the tabu search method. While Hertz & Lahirichi (2009) use tabu search for a patient assignment. Specifically, tabu search is a metaheuristics search method that builds on local search by relaxing its basic rule (Glover & Kochenberger, 2006). Not unlike local search, tabu search takes a potential solution and checks its immediate neighbours in the hope of finding a solution. However, unlike local search, tabu search will accept moves that worsen the solution if no other improving move is available. Besides, the method uses a list of prohibitions (termed tabu list) to discourage the solution from returning to previously visited solutions.

The choice of solution methods is dependent on how complex, large, and computationally cumbersome the problem is. The increase in computer power has also increased the scope of solvable applications. As can be observed in Table 6, early applications mainly deployed Simplex to solve their optimisation problem. More recently, the complexity of solutions is reflected in the type, algorithm of choice and the use of specialised software packages such as CPLEX. As noted earlier, the application of optimisation to mental healthcare is trailing compared to other healthcare settings.

5. Discussion

The application of optimisation to mental healthcare is in its nascent stages. We have assembled a purposefully broad-ranging future research agenda, drawing on several significant trends and characteristics from healthcare literature. For the future development of optimisation models in healthcare, we outline actionable themes such as incorporating uncertainty and risk, timely access to care, continuity of care, multiple care settings, integrated care settings and, new modelling and solution methodologies.

5.1. Incorporating uncertainty and risk in mental health optimisation models

Models are beginning to incorporate dynamic aspects of the healthcare system by integrating sources of uncertainty and risk in application areas such as inventory management, facility location, and planning and scheduling of operating rooms. Uncertainties have been included in optimisation models in several care settings such as cancer care (Mahmoudzadeh et al., 2016), surgical care (Koppka et al., 2018), in the management of operation theatres (Kroer et al., 2018) and home healthcare (Yuan et al., 2015). In the context of mental healthcare, it appears that some studies have incorporated uncertainty either explicitly or implicitly. A recent study has explicitly modelled uncertainty regarding appointment cancellation and no-shows by using patient progress indicators to make no-show predictions (Samorani & LaGanga, 2015). Models built in the context of deinstitutionalisation have incorporated uncertainty implicitly corresponding to funding and budgets. Effectively, uncertainty in mental healthcare optimisation models is lagging in both scope and depth compared to broader healthcare. Particularly challenging to model is the uncertainty associated with diagnosing psychological disorders (discussed in section 2.4), which influences treatment pathways and subsequent treatment outcomes. Furthermore, mental health services' co-location and interdisciplinary nature pose uncertainties regarding the boundaries between services and roles. Indeed, healthcare literature has deemed it necessary to integrate uncertainty to expand the scope of application. Essentially, this assertion extends to mental healthcare.

Risk factors in mental healthcare are predominantly related to the self-destructive behaviour of patients and staff safety relative to specific manifestations of mental illness (discussed in section 2.4). These risk factors are often associated with risk categories, including (but not limited to) individual risk factors, demographic variables, treatment history, and social variables (Franklin et al., 2017). Risk assessment tools are a central practice in mental health services. Often, they are used as a helpful adjunct to inform management plans (Appleby et al., 2018). In mental health optimisation literature, Leff et al. (1986) use a similar approach to categorise patients based on a spectrum of functional levels, starting from "dangerous" to "Recovering". Patients from each category are then assigned to specific service packages. Even so, in recent studies, no such consideration of risk has been considered. In healthcare literature, risks associated with various care settings have been included in optimisation models in multiple contexts. For instance, the risk of surgery cancellation (Y. Wang et al., 2014), operational risk (Ahmadi et al., 2019), and longer procedure times have been modelled. In the context of mental healthcare, future research could look to existing models that incorporate risk. Besides, the inclusion of risk relative to both patients and staff is an essential strand of consideration for future research.

5.2. Models to address timely access for mental health services

Several parallels can be drawn between the service provision of cancer care and specialist mental health care. Recent initiatives to improve specialist mental health services align with some principles that underpin good practice in cancer care (Larkin et al., 2017). While acknowledging clinical differences between the two care systems, it has been argued that comparisons between cancer care and mental illnesses such as psychosis provide a valuable lens to examine service provisions (Larkin et al., 2017). Not unlike mental healthcare – as outlined in section 2.3 – cancer care combines hospital care, outpatient care, and home care (Gospodarowicz et al., 2015). Although cancer treatment is mainly hospital-based, and mental healthcare is mainly community-based. In both cancer care and specialist mental healthcare, the ethos of providing timely access to care is yet another parallel (Mulville et al., 2019; National Academies of Sciences, Engineering, and Medicine, 2018). A substantial amount of research utilising OR methods for cancer treatment planning and scheduling can be found in the literature (Saville et al., 2019).

Despite the rhetoric of providing timely access to care, patients are often unable to access care on time, and long waiting times are a challenging barrier to improving mental health outcomes (British Medical Association, 2017). Instances from cancer care that have also explored improving access to treatment present a possibility for adaptation. Future research could consider optimising the location of treatment centres using performance measures like total demand-weighted distance, and total distance travelled (Cotteels et al., 2012).

5.3. Modelling continuity of care for mental health patients

Continuity of care is considered a prerequisite for providing high-quality care and is regarded as a guiding principle in planning and delivering services in mental healthcare (Biringer et al., 2017; Freeman et al., 2002). This aspect of mental health services warrants further inclusion in model development. Specifically, in home healthcare and outpatient care literature, continuity of care constraints are often used to assign patients to care workers (Ahmadi-Javid, Seyedi et al., 2017; Cissé et al., 2017). Furthermore, continuity of care for mental health patients can be extended to a patient's care pathway across multiple services in the mental healthcare network, which could include social services, community services, outpatient and inpatient mental health services (Slade et al., 2005). When organising treatment pathways, multidisciplinary teams are faced with a similar challenge of ensuring continuity of care. Examples of multidisciplinary planning include modelling capacity fluctuations and planning care pathways (Leeftink et al., 2020). Future research could explore the applicability of such instances to planning mental healthcare service delivery.

5.4. Models to consider multi-layered mental healthcare systems

One of the main characteristics of care settings in mental healthcare is the interconnectedness of services. Also present are multiple types and levels of workers who work in tandem. It is known that mental healthcare is primarily focused on providing care in the community through several channels such as in a patient's home, on the telephone, and at local clinics. In this context, to tackle common mental health issues or complex mental health issues in the community, patients increasingly receive care at their home, by telephone, and at local clinics by "wrapping services" around primary care (Edwards, 2014). Herein teams of multidisciplinary skill-mix mental health staff are developed in collaboration with secondary care, around groups of primary care practices that serve a specified population in a geographic location (World Health Organization, 2018a, 2018c).

From a modelling perspective, incorporating features that are characteristic of complex systems in models is challenging. However, similar structural and workforce issues exist in healthcare literature, which are transferrable to mental healthcare services. For instance, parallels can be drawn from existing applications of optimisation in community services (Palmer et al., 2018), home healthcare (Cissé et al., 2017), outpatient Care (Ahmadi-Javid, Jalali et al., 2017) and owing to the multidisciplinary nature of the teams, from multi-disciplinary planning (Leeftink et al., 2020). Besides, in situations where multiple workers with a mixed skill set are required to provide services to patients in multiple locations, future research could investigate the possibility of applying multi-skilled multi-location models. Such models have been developed to address the food safety inspector scheduling problem (Cheng & Kuo, 2016) and for scheduling airline customer service agents to locations in a large international airport terminal (Kuo et al., 2014).

The integrated nature of mental healthcare services poses another modelling challenge: developing models that aid decision-making across different systems and planning levels. In essence, integrated care delivery involves coordinating services across multiple healthcare professionals, organisations, and sectors and prioritising patient needs and preferences (Tsasis et al., 2012). There is a wide-ranging consensus in extant healthcare optimisation literature to develop models that aid decision-making across integrated systems. An example of optimisation applied to an integrated care system can be found in a study by Braaksma et al. (2014), who present a methodology to plan treatment for a multidisciplinary rehabilitation centre and present an integer linear programming approach to implement combination appointments. Additionally, Marynissen and Demeulemeester (2019) have positioned the MASPH literature discussed in section 2.1.4 as an additional dimension to the spectrum of integrated healthcare. Several authors have encouraged future researchers to build models that capture realistic assumptions (multiple servers, multi-type demand, and uncertainty). This limitation also extends to capturing variability in care pathways. Although modelling the integration of services is an emerging application area, existing models can be adapted to model integrated care in mental healthcare (Nossack, 2022). In addition, future work would need to consider the boundaries between healthcare professionals and organisations and incorporate multi-level modelling and mixed methods, which involve some recognition and appreciation for the dynamic complexity of the mental healthcare system. Future research can be guided by a recent review article on clinical pathway modelling. Aspland et al. (2021) propose a taxonomy of clinical pathway problems to improve the handling of multiple scopes within one model while encouraging interaction between the disjoint care levels.

The findings suggest that future work should consider industrial engineering integrated with OR techniques. So far, this review has identified opportunities from several healthcare settings where optimisation models can be transferred to mental healthcare. Through this analysis, we have established that research gaps that were identified in section 2 can also be extended to mental healthcare service planning. In particular, section 2 shows that models are far from comprehensively tackling complex real-world problems in healthcare planning. Several reviews have highlighted the absence of models that include environmental factors such as patient no-shows, emergencies, resource absenteeism, unpunctuality, unavailability and traffic delays. Moreover, given the disruptions caused by the current public health crisis, researchers call attention to the absence of models that consider factors such as disruption relative to natural disasters, economic or financial crises, and social events.

5.5. *Developing new modelling and solution methodologies to address challenges of mental healthcare delivery*

This review has identified the need to formulate complex models that capture mental healthcare systems. Increasingly, optimisation methods capable of solving complex real-world problems in healthcare are being developed and deployed. By examining the latest advances in healthcare modelling, this section will attempt to carve out methodological avenues for future research in mental healthcare planning.

In mental health care, lack of standardised information technology data sources and limited scientific evidence for mental health quality measures are critical barriers to measuring and improving mental health care quality (Kilbourne et al., 2018). Worldwide, quality of care in mental healthcare is suboptimal with persistent gaps in access to and receipt of mental health services (Demyttenaere et al., 2004; P. S. Wang et al., 2007; Whiteford et al., 2013). Therefore, to close existing gaps, mental healthcare systems worldwide are also rolling out service standards similar to those in physical health services. Services are looking to increase capacity and set up access and waiting time standards (NHS England, 2014). Although significant advances are currently underway to identify mental health care quality measures, several obstacles are yet to be overcome. These systemic factors are challenging to model since quality measures are inextricably linked to measures of performance, which inform model building.

As evidenced earlier, optimisation models for mental healthcare planning are predominantly deterministic; they do not capture the uncertainties inherent in the system. In other strands of healthcare optimisation literature, uncertainty related to service duration, patient preferences, patient arrivals, interruptions etc., have been modelled using methodologies such as stochastic programming and robust optimisation. Specifically, an optimisation problem is stochastic if some or all parameters are uncertain, but they follow a probability distribution (Birge & Louveaux, 2011).

For instance, stochastic programming has been used for staffing and scheduling homecare employees by considering uncertain demand (Restrepo et al., 2020) and for operating room scheduling in the presence of cancellations and resource unavailability (Xiao et al., 2016). On the other hand, in the presence of unreliable data in a system with uncertainty, a robust optimisation model can be used. Such a model aims to make a feasible decision no matter the constraints and is optimal for the worst-case objective function (Gabrel et al., 2014). For instance, physician capacity planning at a tactical level, in the presence of unreliable data and uncertain patient demand, is modelled using robust optimisation (Aslani et al., 2020). Formulating planning problems by utilising such methods could be considered for future research.

More than half the articles under review have used exact solution algorithms, while the rest have employed heuristics, metaheuristics, or hybrid algorithms. Notably, when the time or cost of determining the optimal solution is too large in decision problems, an acceptable and feasible solution is preferred (Capan et al., 2017). In this context, optimisation models in healthcare are increasingly being solved by more than one solution method. Specifically, hybrid optimisation approaches that combine exact and heuristic methods to deal with the complexity are used (Feldman et al., 2014). Additionally, to solve large-scale problems, heuristics and metaheuristics are the methods of choice for their ability to provide satisficing solutions (Saha & Ray, 2019; Volland et al., 2017). While the use of such instances has been found in mental healthcare literature, in comparison to other strands of healthcare literature, it is limited in both size and scope.

Researchers have recently identified the need to take a holistic approach that integrates planning decisions and have developed hybrid models that combine several OR techniques. In particular, forecasting, simulation and optimisation are used in combination for capacity planning in a hospital (Ordu et al., 2020). Metaheuristics are used alongside simulation to schedule walk-in patients in clinics (Amaran et al., 2016; Peng et al., 2014). Such approaches often build on gaps identified in particular strands of research (Uriarte et al., 2017). Notably, such approaches are lacking in mental healthcare research.

Globally, the increased awareness of the unmet need for mental health services is leading to the growth of several strategies that focus on coordination and communication between health services. Such care models are often collectively termed “mental health integration”, “behavioural health integration”, or “integrated care” (Unützer et al., 2020). In such a care setting, multiple stakeholders with diverse perspectives and views are likely to influence decision-making. Therefore, researchers have developed multi-methodology frameworks that combine hard and soft OR methods to gather information and knowledge about the system and help reflect multiple stakeholders’ diversity of concerns (Pessôa et al., 2015). Simulation is often combined with Problem Structuring Methods (PSM) (Sachdeva et al., 2007; Tako & Kotiadis, 2015). More recently, Soft Systems Methodology (SSM) tools were used to structure the medical training problem’s objectives and specifications. The information was then fed to formulate a mixed integer-programming problem (Cardoso-Grilo et al., 2019). It is noteworthy that the combination of optimisation with PSMs is only just beginning in healthcare literature, with only one such application so far.

5.6. Managerial insights

Increasingly, to ensure safe, sustainable, and productive staffing of mental healthcare services, the planning priority is to make sure “the right people, with the right skills, are in the right place at the right time” (Baker & Pryjmachuk, 2016). Central to achieving this goal is appropriate workforce planning and deployment. The planning and deployment of a skilled workforce are some of the most challenging problems a manager faces that have real-life implications. Our review has revealed that most planning models in mental healthcare were used in real world practical contexts. However, we have decidedly established that these models have a narrow scope and use simplified assumptions. As seen in Section 2.3, workforce planning in healthcare is a well-researched application area. Models have considered multiple skills, shifts, and criteria to build realistic models incorporating stochasticity and uncertainty (De Bruecker et al., 2015). Such considerations are missing in mental healthcare models and is a prominent area of future research.

Additionally, when it comes to model building in practice, managers and researchers should be aware of a range of factors that differentiate healthcare modelling from other industries. Factors include the importance of using problem structuring, problems associated with data collection, and interpreting the model and its results (Virtue et al., 2013). The importance of using problem-structuring methods to facilitate stakeholder participation is the focus of many future research directions, also echoed by this article (Júnior & Schramm, 2021). In addition, by drawing on our own experience of building an optimisation model for a mental healthcare service, we acknowledge and confirm the importance of these practical factors described above. Notably, in our experience, problem-structuring methods such as SSM proved invaluable in eliciting stakeholder participation throughout the entire modelling cycle (Ranyard et al., 2015). Equally, we wish to emphasise the effort and difficulty associated with collecting data. We recognise that most services routinely collect crucial data. However, significant resources are required to understand and clean said data before being used in the model (Onggo & Hill, 2014). Likewise, researchers and managers ought to be aware of the intricacies of communicating technical information to stakeholders (Herrera et al., 2016). Problem-structuring and multi-methodology methods have endeavoured to bridge this gap, and optimisation modellers can draw from these studies (Howick & Ackermann, 2011). However, it is worth noting that such applications have developed visually interactive simulation models. In comparison, optimisation models do not have visualisation capabilities and are therefore challenging to translate (Waisel et al., 2008).

6. Conclusion

This paper provides a scoping review of the application of optimisation methodologies in mental healthcare services. Half of the reviewed studies were conducted in the immediate period following deinstitutionalisation (the 1960s onwards). The research appears to have resumed in the past decade. We also survey the landscape on the application of optimisation to healthcare and provide an overview in Table 1. Through this survey, we identify gaps in current literature and highlight opportunities for transferability of existing applications to the context of mental healthcare services. Features associated with mental healthcare are also presented and contrasted with healthcare to identify similar characteristics or problems that have been addressed in other healthcare settings, which have the potential of being transferred.

After establishing the background for the mental healthcare setting, we then conduct a scoping review and classify the identified studies. Articles are organised through a generic analysis of various characteristics. The number of publications associated with mental healthcare planning and delivery is restricted and sporadically distributed compared to physical healthcare, which indicates the limited attention habituated to this aspect of healthcare. We then conduct an in-depth analysis of the optimisation models built for mental health services and find that the models are predominantly deterministic; they do not capture the complexities inherent in the system. We draw parallels between psychological and physical health to identify opportunities for transferability and propose a broad research agenda. Based on the analysis of existing literature, features of mental healthcare services, and the results of our review, we find that although opportunities for transferability exist, gaps in healthcare optimisation literature also extend to mental healthcare. Although COVID-19 is a physical health crisis, it has seeds of a major mental health crisis as well. Mental health services have had to switch to providing care remotely. While such approaches can be effective and scalable, they are not the answer for all mental health needs. Other tried and tested modalities of care continue to be of importance. Good mental health is a critical aspect of recovery from COVID-19. The pandemic could turn into an opportunity to catalyse change and comprehensively address the barriers that have prevented the widespread delivery of efficient services. Indeed, now is the time to expand access to provide cost-effective delivery of effective mental health services. OR techniques have a proven track record for their ability in aiding decision-making at strategic, tactical and operational levels. Healthcare managers can use optimisation models to plan patient pathways, efficiently manage and deploy their workforce, and evaluate the introduction of new treatment modalities such as telemedicine. Through this review, we have outlined a host of future research questions that optimisation modelling can answer. However, we do not assume to have identified all of them. This review is an open call to optimisation modellers and to the OR community to help support future planning of mental health services

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Appendix

Table A1. Search Strategy for Web of Science database.

Database:	**Web of Science**
Strategy:	Field tag **ALL** was used to conduct the search for model types, health, and application area. The search was further **refined** through Web of Science categories for subject areas. The search was restricted to **English** and the timespan was **"All Years"**.
Sub-search categories:	

(a) Model types
ALL = ("optimization" OR "optimisation") OR
ALL = ("mathematical model*" OR "mathematical program*") OR
ALL = ("programming" OR "non-linear programming" OR "nonlinear programming" OR "linear programming") OR
ALL = ("heuristic" OR "metaheuristic")

AND

(b) Subject Categories Limitation
Refined by: WEB OF SCIENCE CATEGORIES: (HEALTH POLICY SERVICES OR HEALTH CARE SCIENCES SERVICES OR MANAGEMENT OR OPERATIONS RESEARCH MANAGEMENT SCIENCE OR COMPUTER SCIENCE SOFTWARE ENGINEERING)

AND

(c) Health
ALL = ("mental health*" OR "community mental health*" OR "psychi*")

AND

(d) Application Area
ALL = ("service*" OR "planning" OR "allocation" OR "scheduling" OR "design")

Table A2. Search Strategy for web of science database.

Database:	**Scopus**
Strategy:	**Keyword search**. TITLE-ABS-KEY search, where KEY includes author keywords and controlled indexed terms in searched databases. Each category was combined with "AND". The search was restricted to English and relevant subject areas.
Sub-search categories:	

(a) Model types
TITLE-ABS-KEY ("optimisation" OR "optimisation") OR
TITLE-ABS-KEY ("mathematical model*" OR "mathematical program*")OR
TITLE-ABS-KEY ("heuristic" OR "metaheuristic") OR
TITLE-ABS-KEY ("program*" W/5 ("linear" OR "non-linear" OR "nonlinear"))

AND

(b) Subject Area Limitation
(LIMIT-TO (SUBJAREA, "COMP") OR LIMIT-TO (SUBJAREA, "BUSI") OR LIMIT-TO (SUBJAREA, "DECI") OR LIMIT-TO (SUBJAREA, "ENGI") OR LIMIT-TO (SUBJAREA, "MATH"))

AND

(c) Health
TITLE-ABS-KEY("mental health*" OR "community mental health*")

AND

(d) Application Area
TITLE-ABS-KEY ("service*" OR "planning" OR "allocation" OR "scheduling" OR "design")