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Limited waiting areas in outpatient clinics: an intervention to incorporate the effect of bridging times in blueprint schedules

Sander Dijkstra,[1] Maarten Otten,[1] Gréanne Leeftink ,[1] Bas Kamphorst,[2] Angelique Olde Meierink,[3] Anouk Heinen,[4] Rhodé Bijlsma,[5] Richard J Boucherie[1]

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[1]Center for Healthcare Operations Improvement and Research (CHOIR), University of Twente, Enschede, Overijssel, The Netherlands
[2]Rhythm BV, Amsterdam, The Netherlands
[3]University Medical Center Utrecht, Utrecht, The Netherlands
[4]Sint Maartenskliniek, Nijmegen, Gelderland, The Netherlands
[5]Department of Medical Oncology, University Medical Center Utrecht, Utrecht, The Netherlands

Correspondence to
Dr Gréanne Leeftink;
a.g.leeftink@utwente.nl

ABSTRACT

Background Distancing measures enforced by the COVID-19 pandemic impose a restriction on the number of patients simultaneously present in hospital waiting areas.

Objective Evaluate waiting area occupancy of an intervention that designs clinic blueprint schedules, in which all appointments of the pre-COVID-19 case mix are scheduled either digitally or in person under COVID-19 distancing measures, whereby the number of in-person appointments is maximised.

Methods Preintervention analysis and prospective assessment of intervention outcomes were used to evaluate the outcomes on waiting area occupancy and number of in-person consultations (postintervention only) using descriptive statistics, for two settings in the Rheumatology Clinic of Sint Maartenskliniek (SMK) and Medical Oncology & Haematology Outpatient Clinic of University Medical Center Utrecht (UMCU). Retrospective data from October 2019 to February 2020 were used to evaluate the pre-COVID-19 blueprint schedules. An iterative optimisation and simulation approach was followed, based on integer linear programming and Monte Carlo simulation, which iteratively optimised and evaluated blueprint schedules until the 95% CI of the number of patients in the waiting area did not exceed available capacity.

Results Under pre-COVID-19 blueprint schedules, waiting areas would be overcrowded by up to 22 (SMK) and 11 (UMCU) patients, given the COVID-19 distancing measures. The postintervention blueprint scheduled all appointments without overcrowding the waiting areas, of which 88% and 87% were in person and 12% and 13% were digitally (SMK and UMCU, respectively).

Conclusions The intervention was effective in two case studies with different waiting area characteristics and a varying number of interdependent patient trajectory stages. The intervention is generically applicable to a wide range of healthcare services that schedule a (series of) appointment(s) for their patients. Care providers can use the intervention to evaluate overcrowding of waiting area(s) and design optimal blueprint schedules to continue a maximum number of in-person appointments under pandemic distancing measures.

WHAT IS ALREADY KNOWN ON THIS TOPIC?

⇒ COVID-19 distancing measures lead to cancellations of patient appointments under (pandemic) distancing measures. Mathematical modelling may support design of blueprint appointment schedules under capacity restrictions.

WHAT THIS STUDY ADDS?

⇒ Our intervention, based on mathematical modelling and computer simulation, in combination with multidisciplinary intervention team meetings, results in a blueprint appointment schedule that takes into account all medical appointment restrictions and maximises a specific target, including, but not restricted to, the number of in-person appointments.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY?

⇒ Clinics with various case mixes may implement our intervention to obtain practically applicable blueprint appointment schedules.

INTRODUCTION

The COVID-19 pandemic has put an enormous strain on healthcare resources.[1–4] Hospitalisation of patients with COVID-19 requires a substantial part of the available beds and an enormous commitment from staff[5 6] and entails new rules of conduct, including 1.5 m distancing measures.[7 8] In the Netherlands, these measures led to cancellations or postponement of appointments (consultations, treatments and surgeries) for non-COVID-19 patients.[3 4]

Distancing measures imposed a limit on the number of simultaneously present patients in shared spaces such as hospital waiting areas. Pre COVID-19, the number of seats in the waiting area was not restrictive for blueprint schedules (also called appointment schedules, templates or rasters) and therefore not taken into account in their design, which typically focused on minimising patient waiting time, resource idle time and overtime.[9]

Pre-COVID-19 blueprint schedules resulted in overcrowded waiting areas under distancing measures. Hospitals were inclined to replace in-person appointments by digital (telephone or video) appointments,[10 11] adjust the blueprint so that larger gaps between patient appointments decreased the risk of patients to overlap[12] and/or cancelled appointments, as not all appointments are suitable for digital replacement and capacity cannot easily be increased.[3 13 14]

An intervention in the blueprint schedule is required to ensure as many patients as possible can visit the clinic under COVID-19 distancing measures. Operations research techniques may be used to optimise and prospectively analyse the impact of blueprint schedules on various outcome measures, before actual implementation in practice.[15] Waiting area occupancy has only emerged as a relevant outcome measure in the literature since the COVID-19 pandemic and is therefore understudied.[16]

This paper evaluates the impact of an intervention, based on mathematical modelling and computer simulation, in combination with multidisciplinary intervention team meetings, to optimise clinics' blueprint schedules and analyse the impact of these schedules on waiting area occupancy from a patient trajectory perspective. As only part of the in-person appointments may be replaced by digital appointments,[10] the intervention specifically aims to schedule all appointments of the pre-COVID-19 case mix either digitally or in person under distancing measures, maximising the number of in-person appointments.

METHOD

Setting

This study involved two clinics of Dutch hospitals: the Rheumatology Clinic of Sint Maartenskliniek (SMK), a specialised hospital for orthopaedic surgery,[17] and the Medical Oncology & Haematology Outpatient Clinic of the University Medical Center Utrecht (UMCU), an academic hospital.[18] The two clinics differ in type of waiting area (centralised and decentralised, respectively) and number of departments (one and two, respectively).

The Rheumatology Clinic of SMK is operated by three nurses, seven physicians and three physician assistants (PAs) per shift. The morning shift is from 8:30 to 12:00 for nurses and from 8:30 to 12:15 for physicians and PAs. The nurses' afternoon shift is from 12:30 to 16:00 and for physicians and PAs from 13:00 to 16:45. Rheumatology patients waiting before or bridging between appointments share a single waiting area with a capacity of 18 seats. During the study, the multidisciplinary intervention team consisted of a project manager, the department head and a planner from SMK's Rheumatology Clinic, a data analysis expert and an optimisation expert.

The medical oncology & haemotology clinic of UMCU consists of two departments: the outpatient clinic where oncologists and haematologists see patients for consultation and the day-care department for chemotherapy and immunotherapy. Four oncologists, three haematologists, one oncology PA and one haemotology PA work at the outpatient clinic per shift. For the oncologists and haematologists, the morning shift is from 8:30 to 12:00 and afternoon shift is from 13:00 to 17:00. For both PAs, the morning shift is from 9:00 to 12:00 and their afternoon shift is from 13:00 to 17:00. The day-care department has 22 beds/chairs, of which 15 are dedicated to medical oncology and 7 to haematology patients. The day-care department operates from 8:30 to 17:00, in which patients can be scheduled consecutively, given a bed/chair is available. UMCU's clinic has two waiting areas. Patients bridging or waiting before a consultation use the 19-seat waiting area of the outpatient clinic, while patients bridging or waiting before a treatment use the 16-seat waiting area of the day-care department. During the study, the multidisciplinary intervention team consisted of a project manager, the department head and a planner of both the medical oncology and the haematology outpatient clinic, the head of the day-care department, two data analysis experts and an optimisation expert.

Definitions

Patient trajectories were defined as the sequence of appointment types a patient has during a single visit to the hospital. As the sequence is predetermined, every appointment type corresponds to a stage. Appointment types were defined as the various modes of appointments for a patient with a specific employee or resource, for example, a patient can see a physician for the first time, have a recurring appointment with a nurse or visit the laboratory for a blood draw.

To discriminate between various forms of waiting, a patient's early arrival time was defined as the time in minutes from first arrival in the waiting area (so from home) to the scheduled starting time of the first appointment. Bridging time was defined as the minimum required time in minutes between the end of an appointment and the start of the subsequent appointment in a patient trajectory, for example, to analyse laboratory test results or prepare drugs. Waiting time was defined as the time in minutes between the scheduled and actual starting time of an appointment, for example, when the physician is still consulting another patient due to patient and/or provider unpunctuality.

Study design

Preintervention analysis and prospective assessment of intervention outcomes were used to review the outcomes on waiting area occupancy and number of in-person consultations (postintervention only).

In the preintervention analysis, measurements were retrospectively taken from October 2019 to February 2020, to determine the clinic's case mix of patient trajectories (see Section Data analysis and handling). The data analyst(s) and optimisation expert analysed the preintervention blueprint schedules that only considered appointment types, evaluated a possible mismatch

between the scheduled and required case mix, as well as the best-case and worst-case waiting area occupancy in the preintervention schedule using our integer linear programming (ILP) model with adapted objective function. The resulting blueprint schedule realisations were evaluated with a Monte Carlo simulation (MCS) to quantify overcrowding of the waiting area(s).

The case mix of the preintervention data analysis was input to an ILP model maximising the number of in-person appointments, and the resulting blueprint schedule was evaluated using an MCS model in an iterative way (see Section Models for the ILP and MCS models and the iterative procedure). The resulting optimised blueprint schedule was discussed in meetings with the multidisciplinary team. These meetings revealed requirements (eg, by visual inspection) that were previously not included in data gathering or restrictions on patient trajectories or number of digital consultations not identified from data or interviews. These elements were added to the input data and/or model restrictions, resulting in a new blueprint proposal to be discussed in the subsequent multidisciplinary team meeting. This discussion session and reoptimisation was repeated twice.

Models

The intervention involved an iterative optimisation and simulation approach, based on ILP and MCS, to obtain a blueprint such that the 95% CI of the number of patients in the waiting area did not exceed available capacity. Both the ILP and MCS models are presented in detail in Otten *et al*[16] and were implemented in Python V.3.9. The ILP was solved using Gurobi V.9.1.0.

The ILP (see online supplemental appendix D) maximises the number of in-person consultations given the waiting area capacity restriction(s) and feasibility constraints: minimal bridging times must be respected, appointments cannot be scheduled outside the identified shifts and appointments cannot overlap or be pre-empted. The ILP assumes patient and provider punctuality (ie, appointment and early arrival times do not deviate from their expectations). The input to the ILP consists of clinic settings, patient trajectories and frequency of patient trajectories in the blueprint, as well as for each patient trajectory the minimum required bridging times, the expected duration of appointment types and the mean early arrival time. The outcome of the ILP is a blueprint schedule that prescribes for each time slot and every resource (eg, nurse, physician, bed) which patient trajectory should be scheduled and whether it should be scheduled in person (preferred in the model) or digitally.

The MCS evaluates the effects of variability in patient arrival times and consultation times on waiting area occupancy. At initialisation all patients are generated according to the ILP blueprint schedule, with an early arrival time and consultation times sampled from normal distributions with specified mean and standard deviation (see Section Data analysis and handling for distribution specifications). These random variables correspond with patient flow through the system as follows. Patients arrive to the waiting area indicated by their early arrival time and scheduled time of their first appointment. At an appointment's starting time, if the corresponding resource is available, the patient is invited from the waiting area, otherwise the patient remains seated in the waiting area. If a patient is not available, the appointment is delayed until the patient becomes available (ie, patients do not overtake each other). If a resource becomes available, the first scheduled patient from the blueprint is invited from the waiting room. After an appointment is completed, the patient either moves to the waiting area until the start of the next appointment in its trajectory (this may include bridging time) or leaves the system if the trajectory is completed. The realisation of the blueprint schedule is simulated for 1000 samples to obtain a 95% CI for the waiting area occupancy over time.

Typically, the number of patients in the waiting area increases due to increased variability. This may cause a blueprint schedule that was feasible in the ILP, to be infeasible under reduced punctuality as shown by the MCS. The iterative optimisation and simulation approach adapts the ILP input parameters by reducing the available waiting area capacity in the time interval in which the MCS model revealed overcrowding and reoptimises. This procedure is repeated until the waiting area occupancy restrictions are met. The approach is detailed in online supplemental appendix C.

In the multidisciplinary intervention team, two additional blueprint requirements were introduced: (1) The case mix of new and recurrent patients over the various resources of similar types should be approximately equal, to ensure good job composition for all employees. (2) For UMCU patients who need day-care treatment, it should be ensured that the remainder of their trajectory can be scheduled within working hours. The first requirement was added as a second objective to the ILP model for both considered clinics. The second requirement was, only for UMCU, incorporated in two ways. First, in the evaluation of the blueprint for only the outpatient clinic, the time to schedule a consultation for a patient following a trajectory with treatment was limited to 8:30–10:30 or 13:00–14:45, as standard in current practice. Second, the joint simulation optimisation of the blueprints of the outpatient clinic and day-care department was considered.

Data analysis and handling

A patient trajectory was initially included if it contained at least one appointment of a type included in the blueprint schedule of the clinic under consideration. From data extracted from the hospital information system (HIS), it was analysed how many patients historically followed these trajectories. If a patient trajectory is logistically unique and occurred, on average, at least once a day, it was included in the blueprint. A patient trajectory is logistically unique if the appointment type or scheduled appointment time in at least one of its stages differs from already included trajectories or if all stages and scheduled

appointment times coincide with an already included trajectory, but bridging time(s) differ(s) (online supplemental appendix B shows how trajectories are combined). The number of occurrences of each included trajectory follows from the historical case mix.

Further input to the ILP are the required appointment times, bridging times and expected early arrival times. Both the required appointment times and bridging times were formulated by expert opinion for each patient trajectory. Physicians indicated for all trajectories the medical possibility for digital consultation and the clinic's management provided the working hours (shifts), number of resources (staff) and capacity of the waiting area(s) of the clinic. The expected early arrival times of patients was determined from HIS data, by comparing the arrival time of patients with the actual realised start time for all realised appointments. We did not discriminate early arrival times for different patient trajectories.

Additional input to the MCS model are the distributions of appointment times and early arrival times. Expert opinion determined that normal distributions suit best. For both SMK and UMCU, early arrival times are assumed to follow a normal distribution with mean 15 min before the scheduled appointment start and a SD of 5 min. For SMK appointment times at all stages were assumed normally distributed with mean equal to the scheduled time and SD equal to 1/3 of this scheduled time. For UMCU, consultation times at the outpatient clinic follow a normal distribution with mean equal to the scheduled time and SD equal to 1/3 of this scheduled time. The appointments at the day-care department are normally distributed with mean equal to the scheduled duration, but with SD equal to 1/8 of the mean, as chemotherapy treatments follow a standardised protocol, which decreases the deviation of its duration.

Statistics

A 95% CI of the waiting area occupancy over time was used to evaluate waiting capacity adherence. Descriptive statistics were provided on relevant input parameters and outcome measures, including number of in-person appointments as a percentage of the day's total number of appointments. Blueprints and absolute waiting area occupancy graphs were used to graphically represent the data.

Patient and public involvement

Patients and the public were not involved in this study.

RESULTS

Preintervention analysis

Case mix of patient trajectories

Table 1 shows the 16 and 26 patient trajectories that are included in the blueprint schedule of, respectively, the Rheumatology Clinic of SMK (34 logistically distinctive trajectories found, of which 16 occurred at least once a day and therefore included) and the Medical Oncology & Haematology Outpatient Clinic of UMCU (112 trajectories found, of which 26 included), including the possibility of digital scheduling as indicated by clinicians, the corresponding minimum bridging times between stages if applicable and the number of occurrences in the blueprint (based on the historical case mix). For UMCU, trajectories A–D belong to medical oncology and trajectories E–I to haematology.

Comparing the historical and the scheduled case mix for UMCU, we concluded that there was a mismatch in supply and demand: the pre-COVID-19 blueprint schedule contained too many slots for trajectories B, E and I and too few slots for trajectories D and F. There was no mismatch between the historical case mix and the scheduled case mix for SMK.

Waiting area occupancy

Figure 1 presents SMK's Rheumatology Clinic pre-COVID-19 blueprint schedule waiting area occupancy outcomes for the worst possible realisation of this blueprint schedule that results in maximum waiting area occupancy (in red), where the waiting area consisting of 18 seats is overcrowded by 22 seats at the peak around 13:00. The best possible realisation that minimises the waiting area occupancy of the pre-COVID-19 blueprint schedule (in blue) overcrowds the waiting area by eight seats in the afternoon due to patient and provider unpunctuality. Online supplemental appendix E provides the corresponding realisations of the worst-case and best-case blueprint schedules. The pre-COVID-19 blueprint includes a few digital consultations (trajectory E—PA) at the end of both the morning and afternoon session of the PAs, that were included in the clinic's pre-COVID-19 blueprint.

Figure 2 presents UMCU's Medical Oncology & Haematology Outpatient Clinic pre-COVID-19 blueprint schedule waiting area occupancy outcomes for the worst-case realisation of this blueprint schedule (in red). Both in the morning and afternoon, a shortage of 11 seats on top of the capacity of 19 seats is faced in the worst case. The waiting room occupancy outcomes of the best-case realisation of the pre-COVID-19 blueprint schedule (in blue) show a shortage of three seats in the late afternoon. Online supplemental appendix E provides the corresponding realisations of the worst-case and best-case blueprint schedules.

Blueprints after intervention for single clinic

For SMK, the COVID-19 blueprint schedule outcomes of our iterative approach are presented in figure 1 (in green). From figure 1, observe that the blueprint schedule adheres at all times to the waiting area capacity restriction of 18 seats. The optimal blueprint includes a number of digital consultations. For nurses, only trajectory I may be replaced by a digital consultation. In the COVID-19 blueprint schedule 50% of these trajectories are scheduled digitally. For rheumatologists and PAs, patient trajectories B, B—PA, and E and E—PA may be replaced by a digital consultation. In the COVID-19 blueprint schedule, respectively, 21%, 17%, 54% and 57% of these trajectories

Table 1 Patient trajectories in Rheumatology Clinic of SMK and Medical Oncology & Haematology Outpatient Clinic of UMCU

	Trajectory	Stage 1	Stage 2	Stage 3	Stage 4	Digital consultation possible?	Bridging time before Stage 2	Bridging time before Stage 3	Bridging time before Stage 4	Number of occurrences in blueprint
Patient trajectories in Rheumatology Clinic of SMK. These occur in blueprint schedules of online supplemental appendix E										
	A			New patient		No	–	–	–	28
	B			Follow-up 1		Yes	–	–	–	28
	C			Follow-up 2	Pharmacy	No	–	–	15	26
	D			Follow-up 2	Blood test	No	–	–	15	34
	E			Follow-up 2		Yes	–	–	–	28
	F	Blood test	Follow-up	Follow-up 2		No	0	30	15	12
	G	Blood test	Follow-up	Follow-up 2	Pharmacy	No	0	30	15	26
	A-PA			New patient		No	–	–	–	6
	B-PA			Follow-up 1		Yes	–	–	–	6
	C-PA			Follow-up 2	Pharmacy	No	–	–	15	12
	D-PA			Follow-up 2	Blood test	No	–	–	15	16
	E-PA			Follow-up 2		Yes	–	–	–	14
	F-PA	Blood test	Follow-up	Follow-up 2		No	0	30	–	12
	G-PA	Blood test	Follow-up	Follow-up 2	Pharmacy	No	0	30	15	6
	H		New patient			No	–	–	–	6
	I		Follow-up			Yes	–	–	–	4
Patient trajectories in Medical Oncology & Haematology Outpatient Clinic of UMCU. These occur in blueprint schedules of online supplemental appendix E										
	A		New patient			Yes	–	–	–	10
	B		Follow-up			Yes	–	–	–	36
	C	Blood test	Follow-up			No	60	–	–	28
	D-60	Blood test	Follow-up	Chemoth. 60 min		No	60	60	–	4
	D-90	Blood test	Follow-up	Chemoth. 90 min		No	60	60	–	9
	D-120	Blood test	Follow-up	Chemoth. 120 min		No	60	60	–	12
	D-210	Blood test	Follow-up	Chemoth. 210 min		No	60	60		9
	E		New patient			Yes	–	–	–	5
	F		Follow-up			No	–	–	–	21
	G	Blood test	Follow-up			No	60	–	–	44
	H-30	Blood test	Follow-up	Chemoth. 30 min		No	60	45	–	6
	H-60	Blood test	Follow-up	Chemoth. 60 min		No	60	45	–	4
	H-120	Blood test	Follow-up	Chemoth. 120 min		No	60	45	–	3
	H-180	Blood test	Follow-up	Chemoth. 180 min		No	60	45	–	1

Continued

Table 1 Continued

	Trajectory	Stage 1	Stage 2	Stage 3	Stage 4	Digital consultation possible?	Bridging time before Stage 2	Bridging time before Stage 3	Bridging time before Stage 4	Number of occurrences in blueprint
	I-30		Follow-up	Chemoth. 30 min		No	–	45	–	2
	I-60		Follow-up	Chemoth. 60 min		No	–	45	–	1
	I-120		Follow-up	Chemoth. 120 min		No	–	45	–	1
	I-180		Follow-up	Chemoth. 180 min		No	–	45	–	1
	J-60			Chemoth. 60 min		No	–	–	–	2
	J-90			Chemoth. 90 min		No	–	–	–	6
	J-120			Chemoth. 120 min		No	–	–	–	7
	J-210			Chemoth. 210 min		No	–	–	–	6
	K-30			Chemoth. 30 min		No	–	–	–	5
	K-60			Chemoth. 60 min		No	–	–	–	4
	K-120			Chemoth. 120 min		No	–	–	–	2
	K-180			Chemoth. 180 min		No	–	–	–	3

For each trajectory, the appointment type per stage is denoted together with the option to replace a consultation with a digital consultation, the minimum bridging times (min) and the number of occurrences required in the blueprint schedule. For SMK, trajectories with identical Stage 3 appointment type have a similar colour tone. For UMCU, trajectories with identical Stage 2 appointment type have a similar colour tone.
SMK, Sint Maartenskliniek; UMCU, University Medical Center Utrecht.

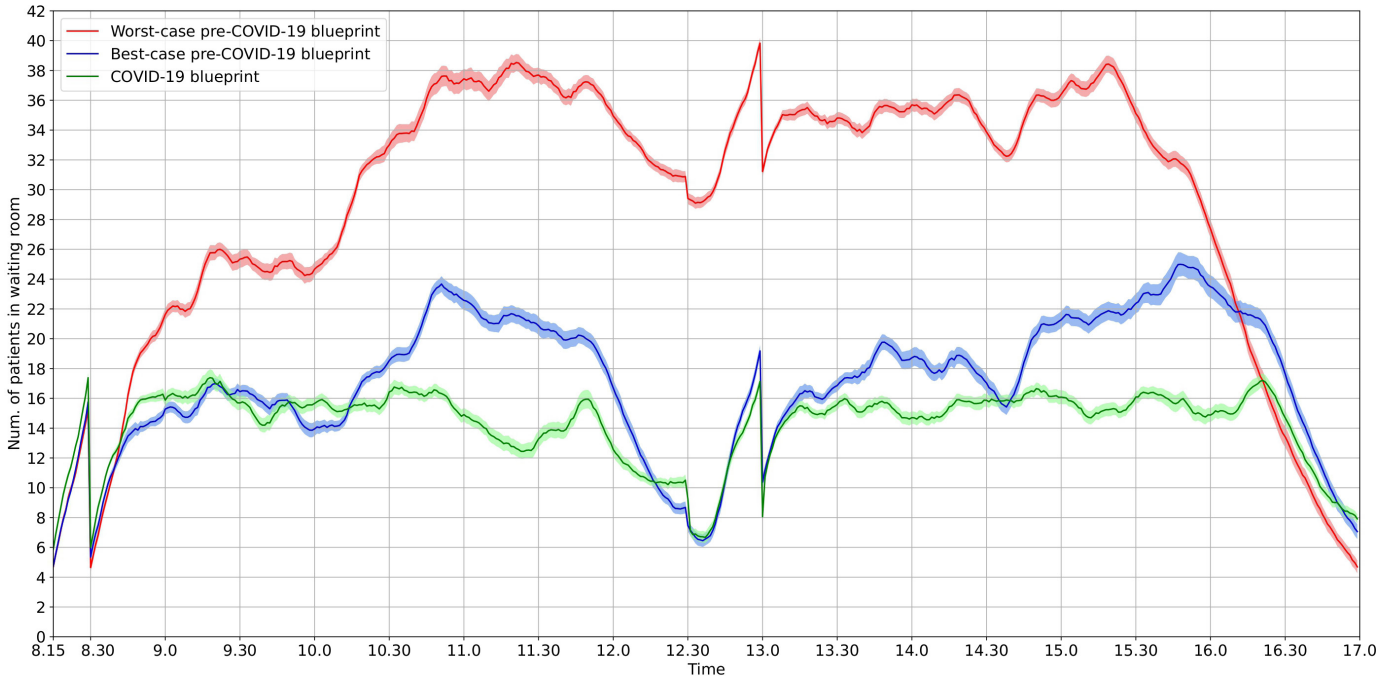

Figure 1 Waiting area occupancy outcomes of the worst-case and best-case realisations of the pre-COVID-19 blueprint schedule and the COVID-19 blueprint schedule resulting from our iterative approach for the Rheumatology Clinic in Sint Maartenskliniek.

are scheduled digitally. In total, of all appointment types, 88% of the consultations are scheduled in person. Under our proposed COVID-19 blueprint schedule, the Rheumatology Clinic of SMK can continue to deliver 100% of their required daily appointments.

For UMCU, the COVID-19 blueprint schedule outcomes are presented in figure 2 (in green). The blueprint schedule adheres at all times to the waiting area capacity restriction of 19 seats. In the optimal blueprint schedule, 58% of trajectory B and 57% of trajectory F consultations are scheduled digitally. In total, this corresponds to 81% of the medical oncology appointments and 87% of the haematology appointments to be scheduled in person, which means that 83% of all appointments can take place

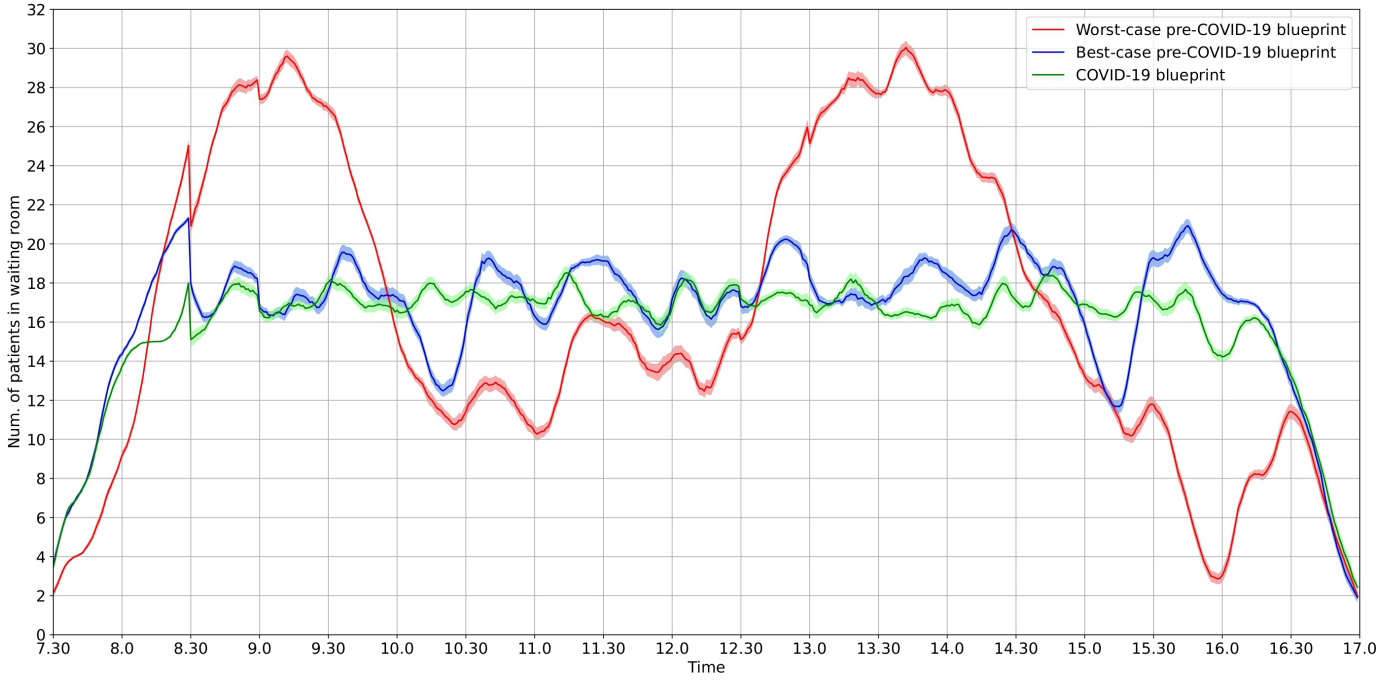

Figure 2 Waiting area occupancy outcomes of the worst-case and best-case realisations of the pre-COVID-19 blueprint schedule and the COVID-19 blueprint schedule resulting from our iterative approach for the Medical Oncology & Haematology Outpatient Clinic in University Medical Center Utrecht.

in person. The Medical Oncology & Haematology Outpatient Clinic of UMCU can continue to deliver 100% of their required daily appointments.

Blueprints after intervention for care trajectory

The multidisciplinary intervention team requested the joint design of the UMCU's outpatient clinic and day-care department. Online supplemental appendix E presents the corresponding COVID-19 blueprint schedules and waiting area occupancy outcomes for both the outpatient clinic and the day-care department.

For medical reasons 100% of the day-care appointments take place in person. Including full information on patient trajectories allows for more flexibility in the outpatient clinic's blueprint, as patients with a day-care treatment may now be scheduled after 10:30 in the morning session or 15:00 in the afternoon session. We observe an improvement in the outpatient clinic blueprint schedule compared with the single clinic case, resulting in 53% of trajectory B and 29% of trajectory F consultations scheduled digitally (58% and 57% in the single clinic case, respectively). In total, 87% of all outpatient appointments can take place in person.

LESSONS AND LIMITATIONS

The preintervention analysis provided evidence for waiting area capacity challenges under COVID-19 measures, especially in more complex and one-stop-shop care settings, which was typically an important reason to scale down regular care. Other reasons for scaling down regular care include limited or reduced availability of resources (hospital personnel, rooms and equipment, for example, due to illness, reallocation of nursing staff to dedicated COVID-19 departments or a hospital's COVID-19 policy) or a change in demand (as patients may avoid care or because hospital referrals and screening programmes were postponed).[3 19] Although not specifically addressed in this research, the effects of limiting the amount of available resources, changing the case mix or reducing the appointment duration and hence increasing the turnover can be prospectively assessed with the intervention. Evaluation and design of optimal blueprint schedules by the iterative simulation and optimisation approach has significant potential in allowing all appointments in the case mix to be scheduled.

Literature suggests that in some cases in-person appointments are preferred over digital ones,[20 21] while in other cases this preference is reversed,[20–22] where the structure of the digital or in-person appointment strongly contributes to its effectiveness.[20 23] Our intervention aims to schedule all appointments of the pre-COVID-19 case mix, maximising the number of in-person appointments, taking into account medical restrictions on appointments that cannot be replaced by a digital alternative. Our blueprint schedules remain feasible when physicians decide to replace additional in-person appointments by digital ones as this reduces the waiting room occupancy.

Data analysis of the case mix in the preintervention analysis might reveal a difference between the historical case mix and the case mix included in the pre-COVID-19 blueprint schedule. This might result in significant waiting lists, significant overbooking or booking on the wrong type of slots. Our data analysis revealed that this was the case for UMCU's Medical Oncology & Haematology Outpatient Clinic, as was also experienced by the department management. In such cases, the historical case mix should be incorporated in the intervention, and blueprint improvement is the compound result of case mix analysis and scheduling optimisation and is expected to result in improved access time performance as well.

The capacity of the waiting room is defined in number of patients. Some patient populations, such as children and elderly, are accompanied during hospital visit, which puts an additional strain on the waiting area. This may be incorporated via the layout of the waiting area, for example, coupled seats for accompanying persons or scaling down of the maximum capacity taking into account the fraction of accompanied patients. Alternatively, planners may defer accompanied patients to times of day at which the expected waiting area occupancy is the lowest in our postintervention blueprint schedule.

The postintervention blueprint schedule prescribes for every time slot which patient trajectory may be scheduled. This blueprint schedule can be included in the agendas of the clinics in the HIS and subsequently used to plan specific patients. We have validated our approach using HIS data in a computer experiment that reveals that our approach allows for more appointments to be scheduled by changing the order of appointments, see figures 1 and 2. The results are used to improve blueprints in SMK and UMCU. Further research is required to evaluate blueprint schedule adherence in practice.

Limitations of our approach are related to our data-driven approach, which requires input data to be of adequate quality. These data requirements include coupling of data in subsequent stages on patient trajectories and data on random delay in appointment durations. However, such data are not always adequately recorded. A further limitation lies in the adaptation of our blueprint schedules in practice, as this requires support by healthcare professionals that may not be used to a data-driven approach. A successful implementation of our approach requires support of a multidisciplinary intervention team that involves healthcare professionals and data experts, as well as heads of the involved department(s). Such a team may be difficult to set up in practice, especially when pressure on healthcare resources is high.

CONCLUSION

We evaluated an intervention for optimal blueprint design, enabling clinics to schedule as many in-person appointments as possible given a maximum waiting area capacity under pandemic distancing measures. The intervention was effective in two case studies, one with a shared

and the other with a dedicated waiting area and different number of interdependent stages in their patient trajectories. While under the pre-COVID-19 blueprint schedules in both cases the waiting areas would have been overcrowded by up to 22 and 11 patients during a large part of the day under COVID-19 distancing measures, prohibiting a large share of appointments to be effectuated, the postintervention blueprint schedule included all appointments in the case mix, of which 88% and 83% were in person (SMK and UMCU, respectively). In the UMCU case study, the fraction of in-person appointments could be increased while still fulfilling the waiting area restrictions when more departments were included in the intervention. The joint design of blueprint schedules for the outpatient clinic and day-care department showed an increase of the number of in-person consultations at the outpatient clinic from 83% to 87%. This showed that trajectory optimisation increases flexibility in the blueprint schedules.

This study showed how the expected waiting area occupancy of blueprint schedules was considerably impacted by three sources: early arrival times for patients who arrive early for their appointment (eg, from home), bridging times for patients who wait in-between appointments (eg, for availability of their test results or for preparation of chemotherapy drugs) and waiting times due to randomness in arrival and appointment times. We assumed that each patient spends their early arrival, waiting and bridging times in the clinic's designated waiting area, which may be either shared over multiple clinics or dedicated to a single clinic.[24] This waiting area may be physically located in the pre-COVID-19 waiting area, but may also be, for example, part of a newly designed centralised waiting area. This study showed that independent of the type of waiting area, the waiting area occupancy can be lowered by adopting our postintervention blueprint schedules.

Our intervention is generically applicable to a wide range of healthcare services with elective care that schedule a (series of) appointment(s) for their patients beforehand. Although this intervention was specifically designed to tackle waiting room overcrowding due to COVID-19 distancing measures, its use extends to possible future pandemics. Post COVID-19, our intervention may also be of considerable value for outpatient clinics that aim to establish blueprint schedules for one-stop-shop care under limited capacity, via the combined capacity restrictions and timing of series of appointments in different stages of the patient trajectories that are key in our approach.

The optimisation and simulation models underlying the intervention are available for the academic and professional community at https://www.utwente.nl/en/choir/research/COVID19-outpatientclinic/.

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ORCID iD

Gréanne Leeftink http://orcid.org/0000-0001-8835-5874

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