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Managing clinic variability with same-day scheduling, intervention for no-shows, and seasonal capacity adjustments

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ABSTRACT

This study investigates demand and capacity strategies for managing clinic variability. These include (i) same-day scheduling to control random walk-ins, (ii) no-show intervention, where the clinic calls advance-booked patients a day before to identify and release cancelled slots to same-day patients, and (iii) adjustments to daily number of appointments for advance-booked patients to match seasonal variations in same-day demand. These strategies are tested over the individual-block/fixed-interval (IBFI) and the Dome appointment rules. Our results show that choosing the appropriate refinements in the order of appointment rules, same-day scheduling, no-show intervention, and capacity adjustment provides maximum improvement. The total cost benefit of demand strategies (i) and (ii) is 7 to 21%, whereas the benefit of capacity strategy (iii) is as high as 6%. Our study affirms the universality of the Dome rule to perform well when combined with the demand and capacity strategies across different environments.

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1. Introduction

Many clinics serve two types of patients on a daily basis – 1) patients who have booked their appointments in advance to consult the doctor at specific times, called "advance-booked" patients and 2) patients who need to consult the doctor on the same day, labelled as "same-day" patients. Advance-booked patients are usually non-urgent cases, and such patients can book future appointments to consult the doctor. In most cases, these are follow-up patients with appointments booked according to their treatment plans plus some new patients with appointments for non-urgent conditions.

New or follow-up patients with urgent conditions will generally need to consult the doctor immediately, preferably on the same day. As more clinics become increasingly patient-centered, the shift is towards serving such patients on the same day. There are two open access options for same-day patients. In the traditional approach, clinics allow patients to arrive unscheduled or randomly as walk-ins. The other option is to implement same-day scheduling, where clinics ask patients to call at the start of each day to schedule an appointment. The goal is to manage or smooth demand through appointments by converting random "walk-ins" into scheduled "call-ins." The potential benefit is shorter wait times for those who are granted appointments; and if no slot is left in the appointment book, they can still walk in randomly but should expect longer wait times.

Another important demand-related variability in appointment systems is the existence of no-shows among advance-booked patients. It is well-documented that advance-booked patients do not always show up for their appointments, and the probability of no-shows increases with lead times to appointments (Gallucci, Swartz, & Hackerman, 2005; Green & Savin, 2008; Liu, Ziya, & Kulkarni, 2010). Several prior studies have investigated strategies on how to best adjust the appointment schedules to alleviate the disruptive effects of no-shows. Some options include overbooking the appointment slots with multiple patients or reducing the appointment interval lengths in anticipation of no-shows. In this study, the consideration of no-shows provides an opportunity to identify potential no-shows of advance-booked patients and release the cancelled slots to same-day patients.

Finally, demand seasonality is an important phenomenon commonly observed in practice, but is not widely addressed in the literature (Gupta & Denton, 2008). For example, primary care clinics often face higher demand during flu seasons while dermatology clinics serve more patients during summer time. This is documented in prior studies that report changing patterns of same-day demand by the day of the week, the month of the year, as well as the hour of the day (Cayirli & Gunes, 2014; Cayirli, Dursun, & Gunes, 2018; Forjuoh et al., 2001). However, in contrast with seasonal demand of

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same-day patients, the demand of advance-booked patients is relatively stable and could even be shaped by the clinics. The appointment times of advance-booked patients are often the result of treatment cycles proposed by the doctors, and the actual appointment times can be shifted within limits of the treatment cycles, without affecting the patients' quality of care. This means that a clinic can shift and offer different number of daily appointment slots to advance-booked patients to smooth out the total patient load per day.

This research investigates strategies to manage clinic variability that arises from the three above sources of variability, ie, random walk-ins of same-day patients, no-shows of advance-booked patients, and demand seasonality. Specifically, we test alternative strategies that are combinations of (i) same-day scheduling, (ii) intervention for no-shows, and (iii) seasonal adjustments to daily capacity. First, we study the impact of same-day scheduling in reducing the adverse effect of random same-day walk-ins. Second, we study the impact of an intervention policy for no-shows that requires the clinic to call advance-booked patients a day before their service day and then release the free slots from cancellations to same-day call-ins. Finally, we investigate adjusting the daily appointment capacity for advance-booked patients in order to better match the seasonal variations in same-day demand. Both strategies (i) and (ii) affect the demand, whereas strategy (iii) affects the capacity, where the ultimate goal is to match demand and capacity. As a result, (i) and (ii) are grouped as "demand" strategies whilst (iii) is grouped as "capacity" strategy. These demand and capacity strategies are tested over two appointment rules that define the basic template of an appointment system in terms of block size and appointment intervals (Cayirli & Veral, 2009). The Individual-Block, Fixed-Interval (IBFI) rule is included as a benchmark rule that is not only well-studied in the literature, but also widely used in practice; The Dome rule, introduced by Cayirli, Yang, and Quek (2012) is included as a "universal" rule, which has the advantage of providing a superior appointment template for different clinic environments defined in terms of no-shows, walk-ins, number of appointments, variation of service-times, as well as the cost ratio that reflects the preferred trade-off between doctor's time and patients' time.

This study provides important guidance to healthcare managers in prioritising their efforts to improve the design of appointment systems. Although it is generally advisable to address the negative effects of all sources of clinic variability, choosing the appropriate refinements in the right order provides maximum gains. For the factor levels tested in our simulation experiments, the largest benefits are achieved by fine-tuning the appointment rule (ie, Dome vs. IBFI), followed by the demand and capacity strategies tested.

Our results affirm and extend the universality of the Dome rule to perform well across different environments when it is combined with different demand and capacity strategies. In terms of demand strategies, the most significant gains are achieved by implementing same-day scheduling to convert random walk-ins into same-day call-ins. This reduces variability by smoothing same-day demand through appointments, resulting in significant improvements in patients' wait times, as well as doctor's idle-time and overtime. The second demand strategy based on an intervention policy for no-shows is also recommended in combination with same-day scheduling. This strategy not only reduces variability due to no-shows, but also offers a higher chance of accommodating same-day demand through rescheduling the open slots released by cancellations. Obviously, both strategies require additional administrative costs in calling advance-booked patients to check on possible cancellations and handling call-ins from same-day patients for appointments. These seem worthwhile as the improvements are significant, even with low proportions of same-day patients and no-shows. On the other hand, our results do not favour capacity strategies unless the demand seasonality is high and the probability of same-day demand is at least 20% of the total demand as tested in our simulation experiments.

The rest of the paper is organised as follows. In Section 2, we provide an overview of the related literature. Section 3 describes the appointment systems tested in our study as combinations of appointment rules with demand and capacity strategies for managing variability. In Section 4, we present the experimental design, simulation model, and performance measures used to compare the alternative strategies and scenarios. Section 5 discusses the results, and Section 6 concludes the paper with a summary of the findings, limitations of current work, and some future directions.

2. Literature review

The reader is referred to surveys by Cayirli and Veral (2009), Gupta and Denton (2008), and Ahmadi-Javid, Jalali, and Klassen (2017) for comprehensive reviews on appointment scheduling. Here, we limit our discussion to studies related to adjusting the appointment systems to deal with variability associated with no-shows, walk-ins, and demand seasonality (Sections 2.1 to 2.3). We also include research related to open-access scheduling

(Section 2.4), since we explicitly compare the traditional approach of allowing random walk-ins versus same-day scheduling which requires patients to call ahead for appointments at the start of each day.

2.1. No-shows

A stream of papers has investigated different strategies to reduce the disruptive effects of no-shows. One approach is to keep the appointment intervals fixed, while assigning multiple number of patients to the same slot, such as double-booking. This requires a subdecision on which particular slots to overbook. Another approach is to shorten the length of appointment intervals proportional to the expected probability of no-shows, while limiting one patient per slot. Vissers (1979) use simulation to compare the two approaches and report that the latter is slightly better because of its sustained effect throughout the clinic session. LaGanga and Lawrence (2007a) investigate overbooking with compressed appointment intervals as their goal is to maximise the net utility of a clinic, balancing the benefits of serving additional patients with the potential costs of patients' wait time and clinic overtime. Their results show that the benefits of overbooking increase for clinics with higher no-show rates, larger clinic size (ie, shorter service times), and lower service time variability In a later study, LaGanga and Lawrence (2007b) use simulation to test a large set of alternative rules that use multiple bookings, as well as compressed appointment intervals, and conclude that the latter approach is preferred due to lower patients' wait times. Kim and Giachetti (2006) develop a stochastic model to determine the optimal daily number of patients' bookings based on the probability density functions of no-shows and walk-ins, yet the decision is not extended to determining the actual appointment times. Studies have also proposed and tested more refined overbooking models that take into account heterogeneous patients' no-show probabilities (Daggy et al., 2010; Muthuraman & Lawley, 2008; Zacharias & Pinedo, 2014), and seasonal variations of no-shows by the time of the day or the day of the week (LaGanga, 2011; LaGanga & Lawrence, 2012). Recently, Liu, Xie, Yang, and Zheng (2018) show that different patient groups exhibit different no-show behaviours. Whilst new or urgent patients are concerned over getting same-day appointments, follow-up or advance-booked patients are more concerned about appointments that match their personal schedules within their treatment cycles. This suggests that a strategy that allows follow-up patients choose their own appointment times and same-day patients immediate access will help to reduce overall no-show rates.

2.2. Walk-ins

Parallel to no-show adjustments, the literature suggests two main approaches to adjusting the appointment schedule for random walk-ins – leave open slots based on the expected number of walk-ins versus lengthen the appointment intervals proportionally. The former approach requires a sub-decision on which specific slots to leave open. Using simulation, Rising, Baron, and Averill (1973) illustrate the benefits of smoothing patient flow by scheduling appointments to complement the arrival pattern of walk-ins. Vissers and Wijngaard (1979) introduce an interval adjustment procedure based on the expected probabilities of walk-ins and no-shows, yet each factor is considered independently. Extending their approach, Cayirli et al. (2012) propose a procedure that adjusts for the combined probabilities of no-shows and walk-ins, and this is incorporated into the formulation of the universal Dome rule that can be parameterised to perform well in different environments. Klassen and Rohleder (1996) test alternative open slot positions to reserve capacity for same-day patients who call for appointments. In a subsequent work, Klassen and Rohleder (2004) expand the open slot analysis to a wider set of options in a multi-period scheduling environment using multiple measures of performance. Their results indicate that the best open slot positions are evenly-spread throughout the day. Morikawa and Takahashi (2017) propose a dynamic method to reduce the negative effects of stochastic walk-in arrivals by assigning scheduled times to walk-ins at the times of their arrivals. Our work is more closely related to the paper by Cayirli and Gunes (2014), which analyses a mixed system with scheduled and walk-in patients, taking into account walk-in seasonality. In a subsequent work, Cayirli et al. (2018) test alternative open slot positions to reserve for walk-ins and conclude that the dominant pattern is evenly-spread with some shift towards the end of the session for higher cost ratios.

2.3. Demand seasonality

Only a few studies have examined demand seasonality or proposed adjustments in the appointment system design for this source of variability (Gupta & Denton, 2008). Forjuoh et al. (2001) predict the demand for same-day appointments in family practice clinics based on historical data organised by the day of the week and month of the year. The authors emphasise the importance of accurate prediction and the need for continuous refinements of demand with seasonal variations. Rohleder and Klassen (2002) address variations in the intra-weekly demand when appointment scheduling decisions are made in a rolling horizon. Their results show that choosing the right scheduling rules depends on the demand loads and choice of performance measures. Koeleman and Koole (2012) model non-stationary emergency arrivals and identify the optimal appointment schedule with a local search algorithm. Open slots are reserved either in the middle or evenly or at the end depending on the relative value of doctor's time to patients' time. Kortbeek et al. (2014) jointly consider the booking process for scheduled patients and the daily in-clinic process that governs the arrivals of scheduled and walk-in patients. They develop a cyclic appointment schedule that accounts for non-stationary walk-in arrivals. Similarly, Cayirli and Gunes (2014) study an appointment system that integrates the access and in-clinic processes, referred to as the macro and micro levels. Using simulation, they evaluate the benefits of seasonal adjustments to daily capacity that vary the number of slots reserved for seasonal walk-ins. Cayirli et al. (2018) extend the model to fully integrate the macro and micro levels for the combined analysis of direct and indirect wait times. In a recent work, Schacht (2018) builds upon Cayirli and Gunes (2014) to study the optimal reconfiguration for seasonal adjustments of the appointment system.

2.4. Open-access (same-day scheduling)

Our study is related to research on open access, also known as same-day scheduling which demands "doing today's work today" (Murray & Tantau, 2000; Murray & Berwick, 2003). This alternative paradigm has the expected benefits of reduced variability due to walk-ins as well as reduced no-show rates given the empirical evidence on the positive correlation between appointment lead times and no-shows (Gallucci et al., 2005). Several studies have addressed the design and implementation of open-access systems (Green & Savin, 2008; Herriott, 1999; Kopach et al., 2007). Robinson and Chen (2010) compare traditional and open access scheduling, and report that open access systems perform significantly better when no-show probability increases with the lead time to appointment and when value of patients' time is high. Chen and Robinson (2014) further study the optimal sequencing and scheduling of routine and same-day patients. Their results are sensitive to the probability of no-shows, probability of same-day patients, workload, and different relative costs of waiting for the two types of patients. Tang, Yan, and Cao (2014) propose an optimal schedule for routine and urgent patients under deterministic service times and develop a heuristic algorithm when service times are exponentially distributed. No-shows are also considered in their model. Xiao, Dong, Li, and Sun (2017) study a similar problem with routine and same-day patients, taking into account revisits by patients as another common source of variability. The authors propose a stochastic programming model to determine the optimal appointment schedule for a given sequence (eg, routine-first, etc.). A number of other studies have also investigated the capacity allocation problem in mixed open access and advanced access systems where the goal is to optimise the ratio of same-day to advance-booked patient slots in the appointment book (Dobson, Hasija, & Pinker, 2011; Gupta & Wang, 2008; Qu, Rardin, Williams, & Willis, 2007; Qu & Shi, 2009, 2011; Wang & Gupta, 2011). Balasubramanian, Muriel, and Wang (2012) and Balasubramanian, Biehl, Dai, and Muriel (2014) study the impact of allowing some flexibility for sharing same-day patients, extending open access to a multi-doctor setting. Huang, Zuniga, and Marcak (2014) use simulation to test a proposed dynamic approach for same-day scheduling of urgent walk-ins on top of a full schedule, taking into account the no-show probabilities of individual patients and the maximum number of urgent patients allowed. Based on the operations of a primary care clinic, Chand, Moskowitz, Norris, Shade, and Willis (2009) investigate how to improve system performance by systematically identifying and reducing the sources of variability in patient arrivals and service times. Using simulation, the authors study the effect of changing over from a traditional appointment system to open access, and observe several improvements, including reduced no-show rates from 40 to 3%.

As an integrative study, we investigate three strategies to adjust the appointment templates, thereby reducing the negative effects of same-day walk-ins, no-shows of advance-booked patients, and seasonal variation of same-day patients. Combining the two demand strategies together integrates the benefits of same-day scheduling with intervention for no-shows. This can be further combined with the capacity strategy to adjust daily capacity to match seasonal changes in same-day demand. By investigating the demand and capacity strategies in different combinations, this study allows a comprehensive analysis of the main and interaction effects of these strategies in managing clinic variability. To the best of our knowledge, this research is the first to address all three sources of variability simultaneously with the goal of refining the appointment systems.

Table 1. Appointment rules tested.

Appointment Rules	Explanation
IBFI	The Individual-Block, Fixed-Interval rule schedules patients individually at fixed intervals, equal to a revised mean service time (μ'). This rule is included as a benchmark, where appointment times (A_i) for i'th patient are calculated as: $A_1 = 0;$ then for $i > 1$, set $A_i = A_{i-1} + \mu'$ for $i = 1, \ldots, N.$ where $\mu' = (1 – PN + PW)\mu$ Note that μ' is a revised mean service time adjusted to include the effects of probability of no-shows (PN) and probability of walk-ins (PW).
Dome	The universal dome rule, shortly Dome, introduced by Cayirli, Yang and Quek (2012) results in "dome-shaped" appointment intervals, where appointment times are calculated as: $A_i = \max\{0, k(i–1)\mu' – \sigma' \cdot \sqrt{i(N+i)/(N–1)}\}$ for $i = 1, \ldots, N.$ The universality of the rule is achieved through the planning constant k, which is set to different values to control the time intervals between appointments to represent different appointment rules for different clinics characterised by the environmental factors, including no-shows (PN), walk-ins (PW), number of appointments per session (N), variability of service times (Cv), and cost of doctor's time to patients' time (CR): $k = \{0.9973 – 0.103[0.005765CR(1–PN) + (CR(1–PN))^{-0.3481}] – 0.10699[Cv^{1.257}] – 0.627[(N(1–PN))^{-0.8579}]$ $– 0.007574[(\lvert CR(1–PW) – 2.143\rvert)^{0.9682} – 0.622CR(1–PW)] + 0.004855(CR^{0.8913})\}^{-1.898}$ Note that both the mean and the standard deviation of service times are adjusted based on the probabilities of no-shows and walk-ins, such that: $\mu' = (1–PN + PW)\mu$ $\sigma' = (1–PN + PW)(\sigma^2 + (PN–PW)^2\mu^2) + PN(1 - PN + PW)^2\mu^2 + PW(2\sigma^2 + (1 + PN–PW)^2\mu^2)$

3. Managing clinic variability

This study investigates how to manage clinic variability through adjustments of the appointment systems when several sources of variability exist. Specifically, the three sources of variability include (i) walk-ins of same-day patients, (ii) no-shows of advance-booked patients, and (iii) demand seasonality.

Our two proposed *demand strategies* include same-day scheduling for "call-ins" with and without no-show intervention. These are compared against the baseline case, where same-day patients arrive randomly as "walk-ins" with no appointments. *Capacity strategies* refer to seasonal adjustments of daily number of appointment slots, compared with the case without any adjustments. These demand and capacity strategies are tested using both Dome and IBFI as the underlying appointment rules. In Section 3.1, we discuss the appointment rules in detail, followed by the demand and capacity strategies in Sections 3.2 and 3.3, respectively.

3.1. Appointment rules

Past research has indicated extensively that no single appointment rule performs well in all environments (Cayirli & Veral, 2009; Gupta & Denton, 2008). Instead, each clinic must evaluate its own environment to choose the right appointment rule. In this study we use the universal Dome rule introduced by Cayirli et al. (2012). Their results show that Dome performs significantly better than some of the popular traditional appointment rules across a wide range of environments. A major advantage of the Dome rule is its "universality", which means that once the levels of no-shows (PN), walk-ins (PW), number of appointments (N), variation of service times (Cv) and cost ratio of doctor's time to patients' time (CR) are specified, it can be parameterised through a planning constant k using a simple formula[1]. To the best of our knowledge, this is one of the best rules in appointment scheduling literature that offer such flexibility; and its performance is robust across other settings that include patient unpunctuality and patient classification (Cayirli & Yang, 2014).

In this study, besides the Dome rule, we include the Individual-Block, Fixed-Interval (IBFI) rule as a benchmark to test the efficacy of our proposed demand and capacity strategies described in Sections 3.2 and 3.3. Combined with different strategies, a traditional rule, such as IBFI, is expected to perform well only in some environments; while Dome can perform well universally because it can be parameterised for different environments. The inclusion of IBFI as a benchmark is to validate the universality of Dome when combined with the demand and capacity strategies. The selected appointment rules represent two alternatives for setting the template of an appointment system in terms of block sizes and interval lengths. While IBFI divides a schedule into fixed, equal intervals, the Dome rule divides a schedule into variable intervals following a dome pattern, where intervals increase initially and then decrease towards the end of a session. The

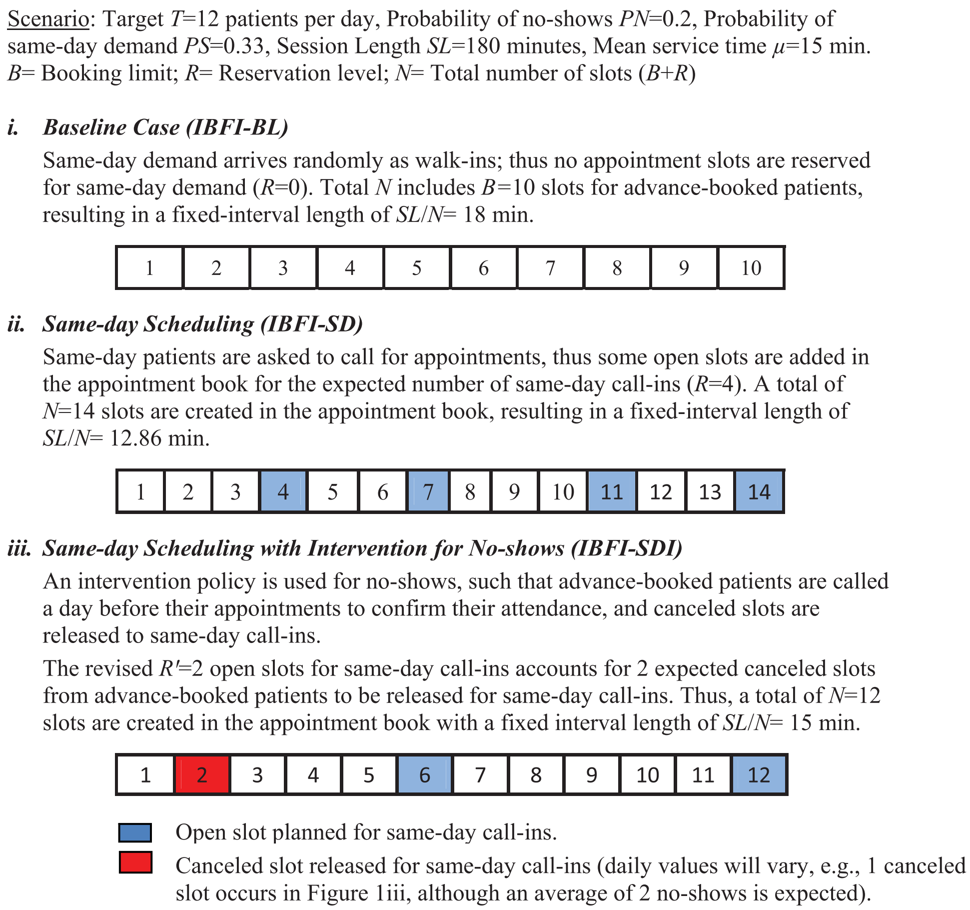


Figure 1. Demand strategies illustrated for the IBFI Rule.

optimality of the dome pattern has been proven by several prior optimisation studies (Denton & Gupta, 2003; Hassin & Mendel, 2008; Kaandorp & Koole, 2007; Klassen & Yoogalingam, 2009; Robinson & Chen, 2003), and a recent work by Jiang, Tang, and Yan (2019) affirms that the optimal intervals remain as a dome pattern under patient unpunctuality. Readers can refer to Table 1 for the formulae for IBFI and Dome rules to compute the appointment times.

3.2. Demand strategies

In this study, we test alternative strategies for managing demand variability in clinics, using same-day scheduling with and without an intervention policy for no-shows. To illustrate the strategies and their effects on the underlying appointment templates, we use a scenario of a clinic with a target to serve $T=12$ patients per session. The mean service time μ per patient is 15 minutes, and the session length (SL) equals 180 minutes to serve 12 patients, ie, 12×15 minutes. The mean numbers of same-day and advance-booked patients served per session are assumed as 4 and 8 patients, respectively. Thus the mean percentage of same-day patients served (PS) – either as walk-ins or call-ins – is 1/3, ie, 33.3%. The total number of slots in the appointment book, N, depends on the demand strategy that allocates the capacity between the two types of patients. The *booking limit* (B) is the number of slots set aside for advance-booked patients, whereas the *reservation level* (R) is the number of slots set aside for same-day patients as call-ins, such that $N=B+R$. Assuming a probability of no-shows (PN) for advance-booked patients as 20%, $B=10$ appointments per session are required for advance-booked patients to serve a mean of 8 advance-booked patients per session with a mean of 2 no-shows. Note that PN is calculated over B, whereas PS is calculated over T. The latter may also be calculated over B, in which case it is denoted as $PS^*=$ 40% to differentiate it from PS. In the case of same-day patients arriving as walk-ins, no appointment slots are reserved or set aside for walk-ins such that $R=0$ and $N=B$. On the other hand, when same-day scheduling exists, R appointment slots are reserved and set aside in the appointment book in anticipation of same-day call-ins.

In the following, we present three alternative demand strategies using the above scenario and the benchmark Individual-Block, Fixed-Interval (IBFI) appointment rule as an example. Figure 1 illustrates how the IBFI appointment template is altered in terms of the number of appointment slots and fixed interval length under each demand strategy, as discussed in detail below:

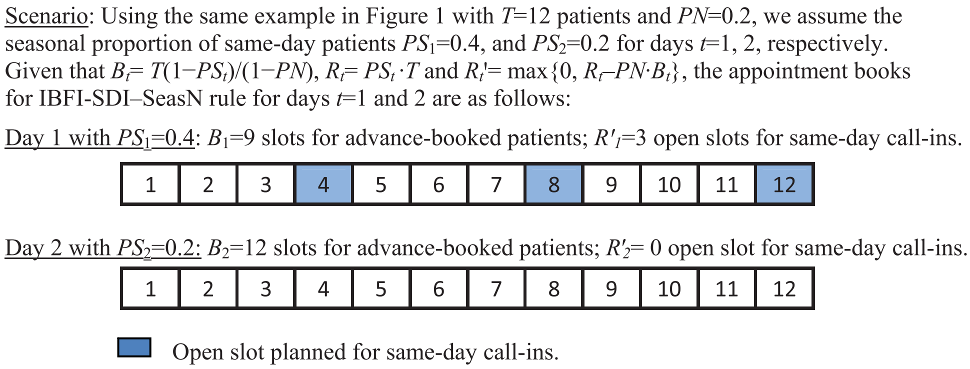


Figure 2. Capacity strategies illustrated for the IBFI-SDI–SeasN rule.

3.2.1. Baseline case (BL)

The baseline case represents the traditional approach where only advance-booked patients are granted appointments while same-day patients arrive randomly as walk-ins. The only decision variable in this case is the *booking limit (B)* for advance-booked patients, which is calculated as:

$$B = T(1 - PS)/(1 - PN). \tag{1}$$

For the scenario with $T = 12$ patients, $PS = 33\%$ and $PN = 20\%$, $B = 10$ appointment slots are created daily for advance-booked patients such that a mean of 8 advance-booked patients are served with a mean of 2 no-shows per day. Since same-day patients arrive as random walk-ins in the baseline case, no reserved slots are created in the appointment book ($R = 0$) for same-day patients, such that a total of $N = B = 10$ appointment slots are created. Figure 1(i) illustrates the baseline case with the IBFI appointment rule. In this example, the IBFI appointment rule divides the session length equally into 10 slots for advance-booked patients, such that each appointment has a fixed interval of 18 minutes (ie, session length $SL = 180$ minutes divided by $N = 10$ appointments). This combination of IBFI appointment rule with Baseline demand strategy is shortly labelled as IBFI-BL.

3.2.2. Same-day scheduling (SD)

As an improvement over the baseline case, same-day scheduling controls the clinic variability arising from random walk-ins. In this implementation, the appointment schedule adds open slots in anticipation of same-day patients, who are asked to call for appointments at the start of each day. This represents a switch from random walk-ins to scheduled appointments for same-day call-ins. The total number of slots *(N)* for each day includes the *booking limit (B)* for advance-booked patients, plus the *reservation level* (*R*) for same-day patients calculated as:

$$R = PS \cdot T. \tag{2}$$

Using the same scenario in Figure 1, the total number of slots is computed as $N = B + R = 14$. This means that 14 slots are created in the appointment book, with $B = 10$ slots for advance-booked patients and $R = 4$ open slots for same-day call-ins. In this example illustrated in Figure 1(ii), using the IBFI appointment rule, the session length is divided equally into 14 slots such that the fixed interval between appointments equals 12.86 minutes, ie, session length $SL = 180$ minutes divided by the total $N = 14$ appointments. The 4 open slots for same-day call-ins are reserved and spread evenly starting from the end slot, such that slots #4, 7, 11, and 14 are kept open for call-ins. This open slot strategy is similar to the patterns proposed in prior studies, where the best slot positions are usually evenly-spread with some shift towards the end when high cost ratios are included (Cayirli et al., 2018; Klassen & Rohleder, 2004). On any day, if there are three callers, slots #4, 7, and 11 are assigned consecutively based on patients' call times while the last slot #14 remains open. If there are more than 4 callers, the first four callers are assigned slots #4, 7, 11, and 14 based on their call times, and subsequent callers are asked to arrive as walk-ins. This combination of IBFI appointment rule with Same-Day scheduling demand strategy is shortly labelled as IBFI-SD.

3.2.3. Same-day scheduling with intervention for no-shows (SDI)

This is a more advanced demand strategy that combines same-day scheduling with an intervention policy for no-shows. This policy requires the clinic to call advance-booked patients before the start of each session, eg, one day before, to confirm their appointments. Cancelled appointments (ie, advance-booked slots with intended no-shows) are then open to same-day patients, who are asked to call the clinic prior to arrivals. As a result, only the expected shortfall in number of slots to match the expected same-day demand is added as open slots for call-ins. The revised reservation level (R') is calculated as:

$$R' = \max\{0, R - PN \cdot B\} \tag{3}$$

where the difference is truncated to zero when the expected no-shows exceed the expected same-day

Table 2. Demand and capacity strategies proposed.

Demand Strategies	Explanation
Baseline (BL)	Baseline strategy where same-day patients arrive randomly as walk-ins (ie, without appointments). *Booking limit* (*B*) for advance-booked patients is calculated as: $$B = T(1 - PS)/(1 - PN) \quad (1)$$ A total $N{=}B$ slots are created in the appointment book.
Same-day Scheduling (SD)	Same-day patients are scheduled as "call-ins", instead of arriving randomly as walk-ins. In addition to the *booking limit* (*B*) for advanced-booked patients [Eq. 1], some slots are added and left open for same-day patients, called the *reservation level* (*R*), calculated as: $$R = PS \cdot T \quad (2)$$ A total of $N{=}B + R$ slots are created in the appointment book to accommodate both types of patients.
Same-day Scheduling with Intervention (SDI)	Same-day scheduling is combined with an intervention policy for no-shows. Advance-booked patients are called a day before their appointments to confirm their attendance, and cancelled appointments are released to same-day call-ins. This additional information is included by revising the *reservation level* R' in Eq. 2 as follows: $$R' = \max\{0, R–PN \cdot B\} \quad (3)$$ where the difference is truncated to zero when expected no-shows exceed expected same-day call-ins. A total of $N{=}B + R'$ slots are created in the appointment book to accommodate both types of patients.
Capacity Strategies	**Explanation**
No Seasonal Adjustments of Capacity (FixN)	The capacity in terms of the *booking limit B* for advance-booked patients and the *reservation level* (*R* or R') for same-day patients is fixed for all days, regardless of the seasonal variations in same-day demand. The mean value of *PS* is used in Eq. 1–3 above.
Seasonal Adjustments of Capacity (SeasN)	*Booking limit* for advance-booked patients (B_t) and *reservation level* (R_t or $R_t{'}$) for same-day patients are adjusted daily for day *t* based on the seasonal variations in proportion of same-day patients (PS_t) over the planning horizon $t = 1,2, .., H$. This means *N, B, PS, R* (or R') in Eq. 1–3 are computed daily as N_t, B_t, PS_t, R_t (or $R_t{'}$) for day *t*. Given that the target number of patients per session (*T*) is fixed, allocating more capacity for advance-booked patients means less capacity for same-day patients on day *t* (or vice versa).

demand (ie, $PN > PS^*$). Using the same scenario in Figure 1, the booking limit $B = 10$ for advance-booked patients remains the same as before using Equation (1). Given that the expected number of same-day patients is 4 and the expected number of cancelled slots is 2, the revised reservation level $R' = 2$. Hence, only two open slots are added and reserved for same-day call-ins as slots #6 and 12, which are evenly-spread starting from the end slot as illustrated in Figure 1(iii). This results in a total number of $N = B + R' = 12$ appointment slots. Using the IBFI appointment rule, these 12 slots are spread evenly through the session length of 180 minutes, with a fixed interval of 15 minutes each.

On a particular day, after calling the advance–booked patients to confirm or cancel their appointments, slot #2 may become available in addition to the added slots #6 and 12. If five patients call for appointments on that day, the sequencing of available slots to call-ins are such that slots #2, 6 and 12 are assigned to the first three callers based on their call times, and the last two callers are asked to arrive randomly as walk-ins. As illustrated in this example, the actual numbers of same-day patients and cancellations can vary every day, even though the averages are 4 and 2 patients per day, respectively. This study tests both cases where the average number of same-day patients is more or less than average no-shows or cancellations. In both cases, the goal is to match the expected number of same-day call-ins to the expected total number of cancelled and added open slots, and thus reduce the chance of random walk-ins. As such, this strategy addresses both sources of variability - walk-ins and no-shows simultaneously, and is hypothesised to further improve the clinic performance. This combination of appointment rule and demand strategy is shortly labelled as IBFI-SDI.

3.3. Capacity strategies

The proposed capacity strategies for managing clinic variability involve seasonal adjustments to the daily capacity, ie, the number of appointments, for same-day and advance-booked patients. To cater to the seasonal variations of same-day demand, there are two alternatives. One alternative is to simply ignore the seasonal fluctuation and fix the daily number of appointments for same-day patients and advance-booked patients, based on the mean demands. This capacity strategy is shortly labelled as FixN strategy. This means that no seasonal adjustment is made, with the "mean" booking limit B for advance-booked patients, and the "mean" reservation level R (or R') for same-day patients fixed for the entire planning horizon (ie, $t = 1,2, ., H$). For the illustrated scenario in Section 3.2 with $T = 12$, $PS = 33.3\%$ (or $PS^* = 40\%$), and $PN = 20\%$, this means that the three demand strategies in Figure 1 offer a fixed $B = 10$ daily appointments for advance-booked patients and a fixed reservation level of $R = 0$ or 4 (or $R' = 2$) daily slots for same-day patients without (or with) the no-show intervention.

The second alternative is to adjust the appointment schedule daily in order to better match the

Table 3. Experimental design.

i. Appointment Systems	
Demand strategy - Capacity strategy	Abbreviations
Baseline (BL) - Fixed N	IBFI-BL-FixN Dome-BL-FixN
Same-day scheduling (SD) - Fixed N	IBFI-SD-FixN Dome-SD-FixN
Same-day scheduling with intervention (SDI) - Fixed N	IBFI-SDI-FixN Dome-SDI-FixN
Baseline (BL) - Seasonal N	IBFI-BL-SeasN Dome-BL-SeasN
Same-day scheduling (SD) - Seasonal N	IBFI-SD-SeasN Dome-SD-SeasN
Same-day scheduling with intervention (SDI) - Seasonal N	IBFI-SDI-SeasN Dome-SDI-SeasN
ii. Environmental factors	
Seasonality of same-day demand (*SEAS*)[a]	Low ($Cv = 0.175$) High ($Cv = 0.304$)
Probabilities of same-day demand & no-shows (*PS-PN*)[b]	20–0%, 20–20%, 10–20%, 20–10%
Cost ratio (*CR*)	1, 5, 20

[a]See Table 4 for details on *SEAS*.
[b]*PS* if calculated over *T*, *PS** if calculated over *N*. *PN* is the probability of advance-booked patients to cancel or miss an appointment; it is assumed that same day call-ins always show up ($PN = 0$).

capacity with the seasonal same-day demand (See Figure 2). This capacity strategy is shortly labelled as SeasN strategy. For the same scenario in Section 3.2, the number of available appointment slots for advance-booked patients, ie, the booking limit is adjusted daily as $B_t = T(1-PS_t)/(1-PN)$ to set aside different daily capacity for the varying mean number of same-day patients, with a mean of $PS_t \cdot T$, where PS_t is the mean proportion of same-day patients on day t. With same-day scheduling, different numbers of open slots are also added daily for same-day patients depending on whether no-show intervention is implemented. When same-day scheduling is implemented without no-show intervention, $R_t = PS_t \cdot T$ slots are added for same-day call-ins on day t. When same-day scheduling is implemented with no-show intervention, $R'_t = \max\{0, R_t - PN \cdot B_t\}$ slots are added for same-day call-ins on day t. Given that the target number of patients served per session (T) is fixed, allocating more slots B_t to advance-booked patients leaves less capacity for same-day patients on day t, and vice versa. Our approach is to allocate the fixed daily capacity T in favour of same-day patients by changing B_t against the direction of same-day demand such that the number of slots for advance-booked patients is reduced (increased) during high (low) seasons of same-day demand. Using the SeasN capacity strategy with IBFI appointment rule and intervention for no-shows demand strategy in Figure 2 with $T = 12$ patients, $PN = 0.2$, but seasonal probability of same-day patients $PS_1 = 0.4$, and $PS_2 = 0.2$ for days $t = 1$ and 2, $B_1 = 12(1-0.4)/(1-0.2) = 9$ appointments for advance-booked patients and $R'_1 = \max\{0, 4.8 - 0.2*9\} = 3$ open slots for same-day call-ins are created for day $t = 1$. Similarly, $B_2 = 12(1-0.2)/(1-0.2) = 12$ and $R'_2 = \max\{0, 2.4 - 0.2*12\} = 0$ appointments are created for advance-booked patients and same-day call-ins, respectively, for day $t = 2$. Obviously, this adjustment reduces (increases) the number of slots B_t for advance-booked patients during high (low) seasons of same-day demand.

The above demand and capacity strategies are tested using the two appointment rules in Table 1, namely the IBFI and Dome rules. Once the total number of appointments N (or N_t) are determined for different demand and capacity strategies, either appointment rule can be used to set the appointment times. Table 2 provides a quick summary of the 3 demand strategies and 2 capacity strategies proposed in this study.

4. Methodology

4.1. Experimental design

As discussed in Section 3, our decision factors include demand and capacity strategies for managing variability, and these are tested using the IBFI and Dome rules. The resulting appointment systems are tested with a common dataset. Pilot simulation runs are used to identify the environmental factors that should be included in the dataset. These factors include demand seasonality (*SEAS*), probability of same-day demand (*PS*), probability of no-shows or cancellations (*PN*), and the cost ratio (*CR*) that indicates the clinic's preference in terms of the relative valuation of doctor's time to patients' time. Clinic size and service time variability are excluded as they do not significantly affect the relative performance or choice of the appointment systems. The environmental factors and factor levels are carefully chosen to cover the full range of environments reported in past studies (Cayirli, Veral, & Rosen, 2008; Cayirli & Gunes, 2014; Klassen & Rohleder, 1996), and further justification for the factor levels is discussed in Sections 4.2 and 4.3. Table 3 summarises the complete experimental design, including the decision rules and environmental factors, as well as the factor levels and abbreviations used. In total, twelve appointment systems are tested (combinations of 2 appointment rules × 3 demand strategies × 2 capacity strategies) under 24 scenarios (2 *SEAS* × 4 *PS-PN* × 3 *CR*) in the dataset.

Table 4. Monthly (MO) and intra-weekly (IW) indices for modeling demand seasonality.

SEAS	**Low (1, 1)** with $\boldsymbol{Cv = 0.175}$:
	MO: I_i= 115-110-120-100-85-90-80-85-95-100-105-115% for months, $I = 1, \ldots, 12$; and
	IW: I_j = 120-95-85-105-95% for days, $j = 1, \ldots, 5$ of the week.
	High (2, 2) with $\boldsymbol{Cv = 0.304}$:
	MO: I_i = 125-115-140-110-75-80-70-75-85-105-100-120% for months, $i = 1, \ldots, 12$; and
	IW: I_j = 130-85-75-117.5-92.5% for days, $j = 1, \ldots, 5$ of the week.

4.2. Simulation model

We use computer simulation to test the appointment systems under a variety of environments. The simulation model is developed with ARENA. The clinic is simulated with a target session length of 225 minutes, representing a single-server system where patients see a doctor for consultation. The target number of patients is fixed at $T = 15$ per session. Lognormal service times are assumed for both advance-booked and same-day patients with a mean service time μ of 15 minutes and a coefficient of variation of 0.5 (ie, $\sigma = 7.5$ min.), consistent with empirical data in past research (Cayirli et al., 2008; Klassen & Rohleder, 1996). Our simulation model is run over 120,000 daily sessions for each of environments tested.

All advance-booked patients and same-day call-ins are assumed to arrive punctually for their appointments. The mean no-show or cancellation probability *PN* of advance-booked patients is tested between 0 to 20%, representative of a fairly respected and well-operated appointment system. In contrast, the no-show probability of same-day call-ins is realistically zero or close to zero as it is highly unlikely that a patient granted an immediate appointment will result in a no-show. This is in parallel with empirical studies that documented significant reduced no-show rates for clinics that shifted towards same-day scheduling (Johnson, Mold, & Pontious, 2007; Murray & Tantau, 2000).

The mean probability, ie, proportion, of same-day demand *PS* is tested at 10% and 20% as most clinics have more follow-up (ie, advance-booked) patients on average than urgent (ie, same-day) patients. This study tests both scenarios with ($PS^* \geq PN$ and $PS^* \leq PN$), where the average number of same-day patients is larger or smaller than the average number of no-shows or cancellations. In line with the growth of open access systems, it is assumed that all walk-ins who arrive before the closing-time of the clinic are accepted. No walk-ins are denied entry, even though they are given lower priority in the queue compared to booked patients. Before he or she is served, a walk-in is made to wait for a maximum of three booked patients served from the queue. However, if only walk-ins are waiting when the doctor becomes idle, they will be seen on a first-come, first-served basis. We believe that this policy is close to what is applied in practice. Furthermore, it is assumed that there is no reneging or balking of patients. This means that all patients, advance-booked and same-day, are served on their day of arrival using overtime, if necessary.

In our simulation model, demand is modelled at the time of patients' arrivals at the clinic, and not at the time when appointments are requested. This simplification allows a comprehensive analysis at micro level, but ignores the indirect wait times for appointments due to seasonal capacity adjustments. Given a fixed daily target number of patients, when higher capacity is reserved for same-day patients at peak demand, the indirect wait times of advance-booked patients for available appointment slots may increase, and vice versa. Investigation of both in-clinic and indirect wait times simultaneously in a fully-integrated model is a possible future extension.

In this study, same-day demand is modelled as a Poisson process with a seasonal pattern that varies by the day of the year, consistent with past research (Cayirli & Gunes, 2014). The mean number of same-day patients for day *t* is calculated as $\lambda_t = \lambda \times I_i^{m} \times I_j^{w},$ where I_i^{m} and I_j^{w} represent the monthly and weekly seasonality indices for month *i* of the year, and day *j* of the week. We simulated a planning horizon of one year, with $H = 240$ days ($i = 12$ months a year, $j = 5$ work-days a week, assuming a seasonal pattern that repeats itself over the four weeks in each month). Table 4 tabulates the details on the intra-weekly and monthly seasonality indices that are used for modelling the demand seasonality. These are based on the same seasonal indices observed and tested by Cayirli and Gunes (2014), including the two extremes of intra-weekly and monthly seasonality; ie, IW, MO= 1, 1 and 2, 2. This results in "low" and "high" demand seasonality with coefficients of variation $Cv = 0.175$ and 0.304, respectively. The following example illustrates how the demand is derived for an environment with same-day demand of "low" intra-weekly (IW) and monthly (MO) seasonality levels ($SEAS = 1,1$). Given the daily target number of patients $T = 15$ and $PS = 0.2$, the mean number of same-day patients $\lambda = 3$ per day. For day $t = 15$ which corresponds to the third Friday of January ($i = 1$ and $j = 5$), the daily expected same-day demand is computed as λ_{15}=3.2775, using indices I_1^{m}=1.15 and I_5^{w}=0.95 from Table 4. The proportion of same-day patients expected on day $t = 15$ can then be computed as $PS_{15} = \lambda_{15}/T = 0.2185$.

Table 5. Total cost performance of IBFI vs. Dome Rule[a] *(All Environments)*.

Demand strategy	Appointment system	TC1	TC5	TC20
i. Baseline Case (BL)	IBFI-BL	20.95	39.68	109.91
	Dome-BL	18.65	37.51	89.54
	% Imp (Dome/IBFI)	10.99%	5.46%	18.53%
ii. Same-Day Scheduling (SD)	IBFI-SD	19.45	35.76	96.96
	Dome-SD	16.00	34.65	85.09
	% Imp (Dome/IBFI)	17.73%	3.13%	12.24%
iii. Same-Day Scheduling w/ Intervention (SDI)	IBFI-SDI	18.07	33.39	90.84
	Dome-SDI	15.28	33.48	82.03
	% Imp (Dome/IBFI)	15.46%	−0.28%	9.70%
Overall Improvement of Dome over IBFI[b]	*Avg. % Imp (Dome/IBFI)*	14.73%	2.77%	13.49%

[a]All values are averaged across the capacity strategies: FixN and SeasN.
[b]Averaged across the demand strategies: BL, SD, and SDI.

4.3. Performance measures

To evaluate the performance of the appointment systems, this study uses the total cost of the clinic represented as follows:

$$\mathrm{Min}\,TC = E[\mathrm{W}])\ + CR(\pi E[\mathrm{O}]\ + E[\mathrm{I}]) \qquad (4)$$

where $E[\mathrm{W}]$ is the mean wait time per patient (advance-booked and same-day patients combined), $E[\mathrm{I}]$ is the mean doctor's idle-time per patient and $E[\mathrm{O}]$ is the mean doctor's overtime per patient. The wait time of a booked patient - either booked in advance or same-day is calculated from the time of appointment, given that all booked patients are assumed to be punctual. On the other hand, the wait time of a walk-in is calculated from the time of his or her arrival since there is no appointment time for walk-in. Idle-time is the time that the server is not serving during session and overtime is the extra time required to serve all patients beyond the target session length. Both physician-related measures, $E[\mathrm{I}]$ and $E[\mathrm{O}]$, are on a per patient basis where the total idle-time (or overtime) in a session is divided by the number of patients seen. The parameter CR represents the relative value of the doctor's time to patients' time. In this study, we use cost ratios $CR = 1$, 5 and 20 to represent clinics with different preference, in terms of the relative value of doctor's time to patients' time. Patient-centred clinics with CR closer to 1 would favour reducing the patients' wait times, whereas physician-centered clinics with CR closer to 20 would prefer reducing the doctor's idle-time and overtime. Between the two extremes, clinics with CR closer to 5 would favour a more balanced approach reducing both patients' wait time and doctor's idle-time and overtime. The chosen cost ratios are similar to those used in prior literature (Cayirli & Gunes, 2014). The other cost parameter, π, is the cost premium of overtime and is fixed at 1.5 in this study to represent the common practice where overtime is penalised 50% over regular time. The overall objective is to minimise the total system cost (TC) including all trade-offs between patients' wait times and doctor's idle-time and overtime.

5. Results and discussion

We present and discuss our results in three parts. In Section 5.1, we compare the performance of the two appointment rules, namely IBFI and Dome. In Section 5.2, we compare the performance of the demand and capacity strategies. As described in Section 3, demand strategies include a baseline case (BL), same-day scheduling without or with the no-show intervention (ie, SD and SDI), whereas capacity strategies indicate whether seasonal adjustments are made on the daily number of slots in expectation of seasonal demand (FixN vs. SeasN policies). Finally, in Section 5.3, we evaluate the impact of the environmental factors (ie., *SEAS*, *PS*, *PN*, and *CR*) on the improvements from the demand and capacity strategies.

5.1. Performance of IBFI and Dome rules

First, we compare the performance of the IBFI and Dome rules, and observe that the environments and capacity strategies affect only the relative performance but not the dominance of Dome over IBFI. The results for the eight environments and two capacity strategies are aggregated to simplify the presentation. Table 5 tabulates the total cost performance of the IBFI and Dome rules under the three cost ratios, namely TC1, TC5, and TC20 for $CR = 1$, 5 and 20, respectively. The results are separated by different demand strategies to reveal any possible interactions with appointment rules.

As shown in Table 5, Dome performs better than IBFI across all three demand strategies, with improvements, ranging from 0% to 19% across different scenarios. There are some interaction effects with the cost ratio as well as the demand strategy. The results show that the total cost improvements due to Dome occur with higher percentages at the extreme cost ratios. This suggests that patient- and physician-centered clinics with extreme cost ratios ($CR = 1$, 20) generally have more to benefit by switching to the Dome rule, compared with clinics with moderate cost ratio ($CR = 5$). The only exception where Dome and IBFI perform almost equally

Table 6. Total cost performance of demand and capacity strategies using Dome rule.

(All Environments) Demand strategy	Appointment system	TC1	TC5	TC20
i. Baseline (BL)	Dome-BL-FixN	18.77	37.68	90.09
	Dome-BL-SeasN	18.52	37.34	88.99
	% Imp (Seas/FixN)	1.35%	0.90%	1.21%
ii. Same-Day Scheduling (SD)	Dome-SD-FixN	16.13	34.81	85.68
	Dome-SD-SeasN	15.88	34.49	84.49
	% Imp (Seas/FixN)	1.56%	0.92%	1.38%
iii. Same-Day Scheduling w/ Intervention (SDI)	Dome-SDI-FixN	15.45	33.85	82.78
	Dome-SDI-SeasN	15.10	33.12	81.28
	% Imp (Seas/FixN)	2.23%	2.17%	1.81%
Overall Improvement of Capacity Strategies[a]	*Avg. % Imp (Seas/FixN)*	1.71%	1.33%	1.47%
Overall Improvement of Demand Strategies[b]	*Avg. % Imp (SD/BL)*	14.18%	7.64%	4.97%
	Avg. % Imp (SDI/SD)	4.53%	3.36%	3.59%
	Avg. % Imp (SDI/BL)	18.07%	10.74%	8.39%
Total Improvement of Demand & Capacity Strategies Combined		19.55%	12.11%	9.78%
Total Improvement of Demand & Capacity Strategies plus Dome Combined		28.33%	16.94%	26.36%

[a]Averaged across demand strategies: BL, SD and SDI.
[b]Averaged across capacity strategies: FixN and SeasN.

well occurs under SDI demand strategy when CR = 5. Apart from this particular case, Dome always outperforms IBFI significantly and it is the preferred appointment rule for all scenarios tested in our study.

In sum, our results affirm the universal dominance of the Dome rule tested under different capacity and demand strategies. The magnitude of the improvement depends mainly on the cost ratio chosen for the valuation of doctor's time relative to patients' time, as well as the demand strategy; yet it is not sensitive to the choice of the capacity strategy used. The overall improvements due to Dome averaged across all demand and capacity strategies are 14.73%, 2.77%, and 13.49% for TC1, TC5, and TC20, respectively (see Table 5). Unlike IBFI which performs well in specific scenarios, the Dome rule performs well across different environments and exhibits its dominance over the traditional appointment rules.

5.2. Performance of demand and capacity strategies

In this section, we evaluate changes in clinic performance due to the demand and capacity strategies implemented over the Dome rule, given its dominance over IBFI in Section 5.1. Table 6 presents the aggregated total cost results averaged over the eight environments for the appointment systems, namely Dome-BL, Dome-SD and Dome-SDI, for both FixN and SeasN capacity strategies. The total cost improvements (%) due to capacity adjustments are indicated as Seas/FixN, comparing Dome-SeasN vs. Dome-FixN under the three different demand strategies, ie, BL, SD, and SDI. The percentage improvements are provided for each level of demand strategy, ie, same-day scheduling over the baseline case (SD/BL), and the incremental improvement due to implementing the intervention policy for no-shows over same-day scheduling(SDI/SD). The total improvement due to same-day scheduling with no-show intervention over the baseline case (SDI/BL) is also provided for the total benefit of implementing both demand strategies together.

As shown in Table 6, the improvements due to capacity adjustments are very small around 1–2%. It is observed that implementing capacity adjustments is increasingly beneficial under the more advanced demand strategies (ie, SDI > SD > BL), indicating some interaction effects between demand and capacity strategies. There are also some variations in improvements due to the effect of cost ratio, yet the overall variations are minor and practically insignificant. The overall percentage improvements for capacity adjustments averaged over the three demand strategies are 1.71%, 1.33%, and 1.47%, indicating the largest benefits for patient-centered clinics with $CR = 1$.

In terms of demand strategies, larger improvements are observed for shifting from the baseline case to more advanced strategies with same-day scheduling. As shown in Table 6, the overall total cost improvements for shifting from the baseline case to same-day scheduling (SD/BL) are around 14.18%, 7.64%, and 4.97% as the cost ratio increases (averaged across the FixN and SeasN capacity strategies). Our results show that same-day scheduling is always better than the baseline case under all scenarios when implemented with the Dome rule. Therefore, rather than letting same-day patients walk into a clinic randomly, advising them to call for same-day appointments improves clinic performance significantly. The incremental benefits due to the intervention policy for no-shows (SDI/SD) are around 3–4%, such that the combined benefits (SDI/BL) are 18.07%, 10.74%, and 8.39% for $CR = 1$, 5 and 20, respectively (See Table 6). This suggests that fine-tuning the appointment systems through more advanced demand strategies is beneficial in improving clinic performance. However, these improvements show diminishing returns as the cost ratio increases. It also indicates that patient-centered clinics ($CR = 1$) have the most to benefit from the demand strategies tested over the Dome rule.

Finally, the total improvement achieved in total cost due to switching from Dome-BL-FixN to Dome-SDI-SeasN, including the benefits of *both* demand and capacity strategies, is 19.55% (ie, TC1 = 18.77 vs. 15.10), 12.11% and 9.78% for cost ratios $CR = 1$, 5 and 20, respectively. If we extend to include the benefits of Dome, ie, switching from IBFI-BL-FixN to Dome-SDI-SeasN, the total cost improvements are 28.33%, 16.94%, and 26.36% as the cost ratio increases.

Although omitted for sake of brevity, the same analysis is conducted using the IBFI rule. The total improvement due to *both* demand and capacity strategies, measured as the change from IBFI-BL-FixN to IBFI-SDI-SeasN is 14.88%, 16.92%, and 18.37% for $CR = 1$, 5 and 20, respectively. Thus the improvements are more uniform under the IBFI rule. Similar to Dome, improvements due to capacity adjustments are only marginal around 1–2% for IBFI. These findings affirm the advantages of demand and capacity strategies regardless of the underlying appointment template used. Overall, we conclude that the largest improvements occur by combining Dome with demand strategies, whereas capacity adjustments provide relatively marginal benefits for the scenarios investigated in our study.

5.3. Impact of environmental factors

We expand the analysis in Sections 5.1 and 5.2 to individual environments in order to analyse the impact of different environmental factors, including demand seasonality (*SEAS*), probability of same-day demand (*PS*), and probability of no-shows or cancellations in case of intervention (*PN*), and cost ratio (*CR*). The goal is to identify the environments under which the more advanced appointment systems are most beneficial and thus worthwhile to implement despite their added complexity. We hereby limit our environmental analysis to the Dome rule, which has consistently outperformed IBFI under all scenarios, as discussed in Section 5.1. The results for the demand and capacity strategies are presented in Sections 5.3.1 and 5.3.2, respectively, for the eight clinical environments tested in our simulation experiments. Tables 7 and 8 tabulate the corresponding results for specific combinations of *SEAS*, *PS-PN* that define a specific environment (eg, Env#1: *SEAS*=High, $PS = 20\%$ and $PN = 0\%$).

5.3.1. Impact of environmental factors on demand strategies

In Table 7, we present the total cost (%) improvements due to the demand strategies calculated for the effects of same-day scheduling over the baseline case (SD/BL), same-day scheduling with no-show intervention over the baseline case (ie, SDI/BL), as well as the incremental effect of no-show intervention over same-day scheduling (ie, SDI/SD). For sake of simplicity, the results for the two capacity strategies (ie, FixN and SeasN) are aggregated as their interactions with the demand strategies and environmental factors are parallel. We discuss the effects of the environmental factors (*SEAS*, *PN-PS*, *CR*) on each demand strategy separately as follows:

5.3.1.1. Demand strategy: Same-day scheduling (SD). Same-day scheduling is beneficial under all environments tested in our simulation experiments, although the benefits vary widely depending on the specific environment. The total cost improvements (SD/BL) range from 2% to 18% (See Table 7 and Figure 3(i)). As one would expect, the higher the probability of same-day demand (*PS*), the higher the benefits. However, the effect of *PS* is also mitigated by the existence of no-shows (*PN*). This is observed in the ranking of SD/BL improvements from highest to lowest in environments with *PS-PN* levels of 20–0%, 20–10%, 20–20%, and 10–20%. Thus there is more value in same-day scheduling when higher number of patients are switched from walk-ins to call-ins, especially when there is little or no relief from no-shows to absorb the random congestion from walk-ins. Furthermore, these improvements decrease as the cost ratio (*CR*) increases, and this is parallel for all environments tested (Figure 3(i)). This suggests that it is more beneficial to implement same-day scheduling with the Dome rule in patient-centered clinics that place high value on patients' time, relative to doctor's time. On the other hand, the effect of demand seasonality (*SEAS*) on the impact of same-day scheduling is very minor and practically insignificant. Overall, we conclude that it is most beneficial to implement same-day scheduling in clinics, where the expected *PS-PN* difference is high and *CR* is low, yet *SEAS* matters little.

5.3.1.2. Demand strategy: Same-day scheduling with no-show intervention (SDI). The second demand strategy is same-day scheduling implemented with no-show intervention. Table 7 tabulates the incremental benefits of no-show intervention calculated over same-day scheduling (ie, SDI/SD), as well as the cumulative effect of same-day scheduling with no-show intervention over the baseline case (ie, SDI/BL). Since SD/BL is already discussed in Section 5.3.1.1, we hereby

Table 7. Total cost performance of demand strategies by environment.

	Env# 1			Env# 2			Env# 3			Env# 4		
Appointment system	*SEAS*=H *PS* = 20%, *PN* = 0%			*SEAS*=H *PS* = 20%, *PN* = 20%			*SEAS*=H *PS* = 10%, *PN* = 20%			*SEAS*=H *PS* = 20%, *PN* = 10%		
i. Baseline case (BL)	TC1	TC5	TC20	TC1	TC5	TC20	TC1	TC5	TC20	TC1	TC5	TC20
Dome	17.525	34.22	81.635	20.07	40.54	96.985	18.02	37.605	89.405	19.14	37.955	91.3
ii. Same-day scheduling (SD)												
Dome-SD	14.465	30.93	75.985	17.195	37.335	92.285	16.635	36.365	87.875	15.915	34.295	85.445
% $Imp^{SD/BL}$	**17.46%**	**9.61%**	**6.92%**	**14.32%**	**7.91%**	**4.85%**	**7.69%**	**3.30%**	**1.71%**	**16.85%**	**9.64%**	**6.41%**
iii. Same-day scheduling w/ Int (SDI)												
Dome-SDI	14.465	30.93	75.985	16.17	36.06	87.785	15.57	34.43	83.015	15.13	32.86	82.6
% $Imp^{SDI/SD}$	**0.00%**	**0.00%**	**0.00%**	**5.96%**	**3.42%**	**4.88%**	**6.40%**	**5.32%**	**5.53%**	**4.93%**	**4.18%**	**3.33%**
% $Imp^{SDI/BL}$	**17.46%**	**9.61%**	**6.92%**	**19.43%**	**11.05%**	**9.49%**	**13.60%**	**8.44%**	**7.15%**	**20.95%**	**13.42%**	**9.53%**
	Env# 5			Env# 6			Env# 7			Env# 8		
Appointment system	*SEAS*=L *PS*=20%, *PN*=0%			*SEAS*=L *PS*=20%, *PN*=20%			*SEAS*=L *PS*=10%, *PN*=20%			*SEAS*=L *PS*=20%, *PN*=10%		
i. Baseline case (BL)	TC1	TC5	TC20	TC1	TC5	TC20	TC1	TC5	TC20	TC1	TC5	TC20
Dome	17.425	34.09	81.01	19.965	40.375	96.315	17.98	37.505	89.165	19.035	37.795	90.5
ii. Same-day scheduling (SD)												
Dome-SD	14.365	30.82	75.42	17.075	37.1	91.525	16.575	36.255	87.58	15.78	34.07	84.565
% $Imp^{SD/BL}$	**17.56%**	**9.59%**	**6.90%**	**14.48%**	**8.11%**	**4.97%**	**7.81%**	**3.33%**	**1.78%**	**17.10%**	**9.86%**	**6.56%**
iii. Same-day scheduling w/ Int (SDI)												
Dome-SDI	14.365	30.82	75.42	16.04	35.92	87.065	15.49	34.23	82.625	14.975	32.615	81.72
% $Imp^{SDI/SD}$	**0.00%**	**0.00%**	**0.00%**	**6.06%**	**3.18%**	**4.87%**	**6.55%**	**5.59%**	**5.66%**	**5.10%**	**4.27%**	**3.36%**
% $Imp^{SDI/BL}$	**17.56%**	**9.59%**	**6.90%**	**19.66%**	**11.03%**	**9.60%**	**13.85%**	**8.73%**	**7.33%**	**21.33%**	**13.71%**	**9.70%**

Table 8. Total cost performance of capacity strategies by environment.

i. Demand Strategy: Baseline Case (Dome-BL)

Appointment system	Env# 1			Env# 2			Env# 3			Env# 4		
	SEAS=H *PS* = 20%, *PN* = 0%			*SEAS*=H *PS* = 20%, *PN* = 20%			*SEAS*=H *PS* = 10%, *PN* = 20%			*SEAS*=H *PS* = 20%, *PN* = 10%		
i. Baseline (BL)	TC1	TC5	TC20	TC1	TC5	TC20	TC1	TC5	TC20	TC1	TC5	TC20
Dome-FixN	17.72	34.48	82.60	20.26	40.83	97.98	18.13	37.77	89.71	19.39	38.34	92.50
Dome-SeasN	17.33	33.96	80.67	19.88	40.25	95.99	17.91	37.44	89.10	18.89	37.57	90.10
% *Imp (Seas/FixN)*	**2.20%**	**1.51%**	**2.34%**	**1.88%**	**1.42%**	**2.03%**	**1.21%**	**0.87%**	**0.68%**	**2.58%**	**2.01%**	**2.59%**
	Env# 5			Env# 6			Env# 7			Env# 8		
	SEAS=L *PS*=20%, *PN*=0%			*SEAS*=L *PS*=20%, *PN*=20%			*SEAS*=L *PS*=10%, *PN*=20%			*SEAS*=L *PS*=20%, *PN*=10%		
i. Baseline (BL)	TC1	TC5	TC20	TC1	TC5	TC20	TC1	TC5	TC20	TC1	TC5	TC20
Dome-FixN	17.47	34.06	81.16	20.02	40.44	96.58	18.07	37.67	89.39	19.11	37.85	90.76
Dome-SeasN	17.38	34.12	80.86	19.91	40.31	96.05	17.89	37.34	88.94	18.96	37.74	90.24
% *Imp (Seas/FixN)*	**0.52%**	**−0.18%**	**0.37%**	**0.55%**	**0.32%**	**0.55%**	**1.00%**	**0.88%**	**0.50%**	**0.78%**	**0.29%**	**0.57%**

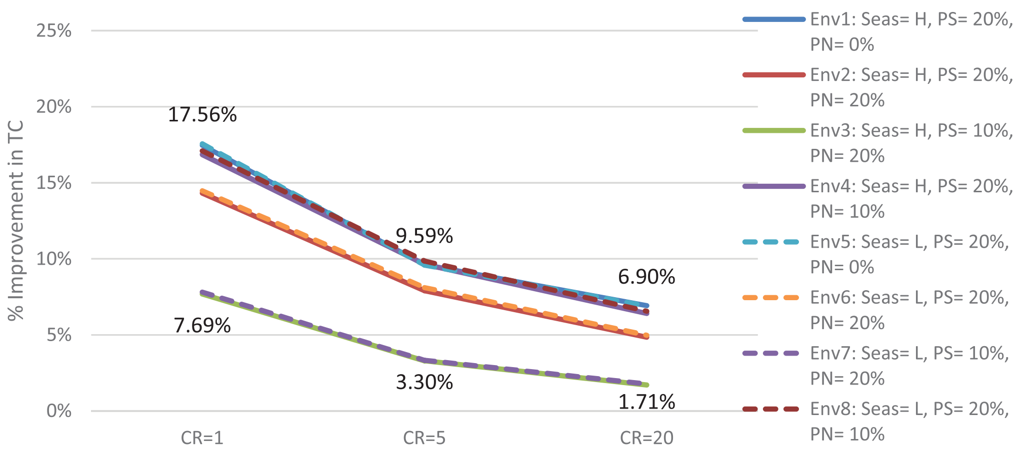
ii. Demand Strategy: Same-Day Scheduling (Dome-SD)

Appointment system	Env# 1			Env# 2			Env# 3			Env# 4		
	SEAS=H *PS* = 20%, *PN* = 0%			*SEAS*=H *PS* = 20%, *PN* = 20%			*SEAS*=H *PS* = 10%, *PN* = 20%			*SEAS*=H *PS* = 20%, *PN* = 10%		
ii. Same-Day Scheduling (SD)	TC1	TC5	TC20	TC1	TC5	TC20	TC1	TC5	TC20	TC1	TC5	TC20
Dome-SD-FixN	14.69	31.2	77.08	17.4	37.62	93.33	16.65	36.53	88.2	16.26	34.75	86.92
Dome-SD-SeasN	14.24	30.66	74.89	16.99	37.05	91.24	16.62	36.2	87.55	15.57	33.84	83.97
% *Imp (Seas/FixN)*	**3.06%**	**1.73%**	**2.84%**	**2.36%**	**1.52%**	**2.24%**	**0.18%**	**0.90%**	**0.74%**	**4.24%**	**2.62%**	**3.39%**
	Env# 5			Env# 6			Env# 7			Env# 8		
	SEAS=L *PS*=20%, *PN*=0%			*SEAS*=L *PS*=20%, *PN*=20%			*SEAS*=L *PS*=10%, *PN*=20%			*SEAS*=L *PS*=20%, *PN*=10%		
ii. Same-Day Scheduling (SD)	TC1	TC5	TC20	TC1	TC5	TC20	TC1	TC5	TC20	TC1	TC5	TC20
Dome-SD-FixN	14.41	30.7	75.39	17.11	37.12	91.76	16.57	36.4	87.77	15.92	34.13	84.97
Dome-SD-SeasN	14.32	30.94	75.45	17.04	37.08	91.29	16.58	36.11	87.39	15.64	34.01	84.16
% *Imp (Seas/FixN)*	**0.62%**	**−0.78%**	**−0.08%**	**0.41%**	**0.11%**	**0.51%**	**−0.06%**	**0.80%**	**0.43%**	**1.76%**	**0.35%**	**0.95%**

iii. Demand Strategy: Same-Day Scheduling with Intervention (Dome-SDI)

Appointment system	Env# 1			Env# 2			Env# 3			Env# 4		
	SEAS=H *PS* = 20%, *PN* = 0%			*SEAS*=H *PS* = 20%, *PN* = 20%			*SEAS*=H *PS* = 10%, *PN* = 20%			*SEAS*=H *PS* = 20%, *PN* = 10%		
iii. Same-Day Scheduling w/ Int (SDI)	TC1	TC5	TC20	TC1	TC5	TC20	TC1	TC5	TC20	TC1	TC5	TC20
Dome-SDI-FixN	14.69	31.20	77.08	16.59	37.26	89.68	15.64	34.64	83.33	15.38	33.26	83.94
Dome-SDI-SeasN	14.24	30.66	74.89	15.75	34.86	85.89	15.50	34.22	82.70	14.88	32.46	81.26
% *Imp (Seas/FixN)*	**3.06%**	**1.73%**	**2.84%**	**5.06%**	**6.44%**	**4.23%**	**0.90%**	**1.21%**	**0.76%**	**3.25%**	**2.41%**	**3.19%**
	Env# 5			Env# 6			Env# 7			Env# 8		
	SEAS=L *PS*=20%, *PN*=0%			*SEAS*=L *PS*=20%, *PN*=20%			*SEAS*=L *PS*=10%, *PN*=20%			*SEAS*=L *PS*=20%, *PN*=10%		
iii. Same-Day Scheduling w/ Int (SDI)	TC1	TC5	TC20	TC1	TC5	TC20	TC1	TC5	TC20	TC1	TC5	TC20
Dome-SDI-FixN	14.41	30.70	75.39	16.27	36.63	87.97	15.56	34.47	82.85	15.04	32.64	81.96
Dome-SDI-SeasN	14.32	30.94	75.45	15.81	35.21	86.16	15.42	33.99	82.40	14.91	32.59	81.48
% *Imp (Seas/FixN)*	**0.62%**	**−0.78%**	**−0.08%**	**2.83%**	**3.88%**	**2.06%**	**0.90%**	**1.39%**	**0.54%**	**0.86%**	**0.15%**	**0.59%**

i. Effect of Same-day Scheduling over Baseline Case (SD/BL)



ii. Incremental Effect of No-Show Intervention (SDI/SD)

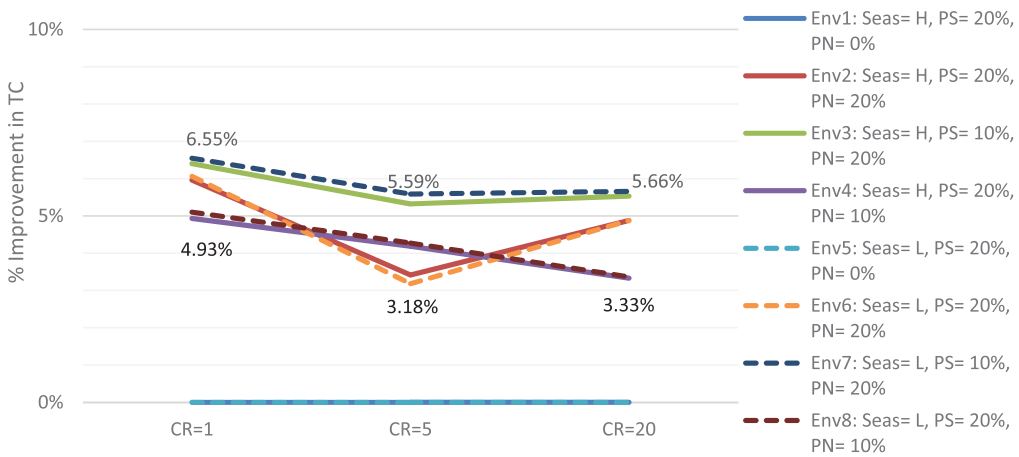


Figure 3. Total cost ımprovements (%) due to demand strategies (*by Environment*). i. Effect of same-day scheduling over baseline case (SD/BL). ii. Incremental effect of no-show intervention (SDI/SD).

focus our discussion on the incremental benefits (see Figure 3(ii)). First of all, the incremental benefits due to no-show intervention are around 3–7% (SDI/SD) with the combined benefits around 7% to 21% over the baseline case (SDI/BL). Note that this excludes Env#1 and #5, where the effect of no-show intervention is zero since appointment systems with or without intervention converge when $PN = 0$. Environments with PS-$PN = 10$–20%; 20–20%, and 20–10% result in decreasing benefits from no-show intervention, although some interaction is observed with the effect of the cost ratio. When PS-$PN = 10$–20% and 20–20%, *all* call-ins are buffered solely by released slots from cancellations, with no open slots added. PS-$PN = 10$–20% also leads to higher benefits from no-show intervention than 20–20%, as the chance of matching demand and capacity improves when there are more expected cancelled slots than call-ins ($PN > PS$). This decreases the probability of (excess) same-day demand arriving as random walk-ins, considering the daily fluctuations around the average *PN* and *PS*. On the other hand, when PS-$PN = 20$–10%, half of the expected call-ins are buffered by added open slots and the other half by possible cancellations. The benefit of no-show intervention is thus lower when *PN* is lower, and when $PS > PN$ as part of the call-ins is buffered by added open slots. The effect of *CR* on no-show intervention is fairly uniform, although exceptions occur for $CR = 5$, where the benefits are lowest for PS-$PN = 20$–20% instead of 20–10% (see Figure 3(ii)). Finally, the effect of *SEAS* on the improvements due to no-show intervention is not significant. These findings suggest that the choice of no-show intervention policy is mainly dependent on *PS-PN* combination, and it can be made independent of *SEAS* and *CR*.

5.3.2. Impact of environmental factors on capacity strategies

Table 8 presents results on the value of capacity strategies under all environments and across all demand strategies (ie, BL, SD, SDI). The total cost (%) improvements due to implementing seasonal N are shortly denoted as SeasN/FixN. This approach allows a complete analysis of the interaction effects among the environmental factors and decision factors. Our findings indicate that there are lower

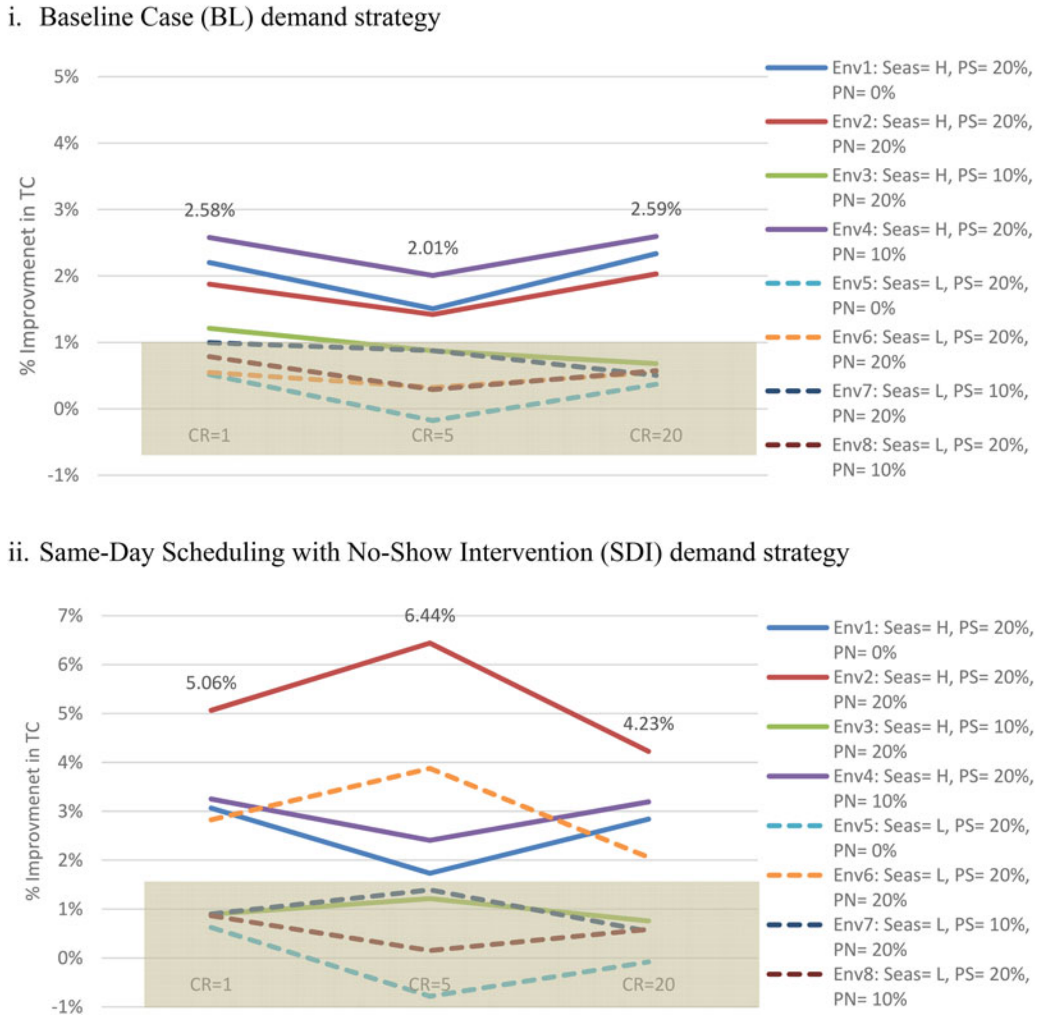


Figure 4. Total cost improvements (%) due to capacity strategies (*by Environment*). i. Baseline case (BL) demand strategy. ii. Same-day scheduling with no-show intervention (SDI) demand strategy.

benefits from implementing capacity strategies compared with demand strategies for the factor levels tested in our study. Specifically, the percentage improvements in total cost (ie, SeasN/FixN) range from around 0 to 6%. Consistent with our aggregate results discussed in Section 5.2, seasonal capacity adjustment is increasingly more beneficial under the more advanced demand strategies (see Table 8 and Figure 4). The improvements due to seasonal capacity adjustments also increase in environments with high *SEAS* and high *PS*, regardless of the demand strategy used. This is expected as higher variations of seasonal demand[2] offer greater potential to seasonally adjust the daily capacity for same-day patients. On the other hand, total cost improvements are generally negligible in scenarios with low *SEAS* and/or low *PS*. In such cases, it is best not to over-react and implement capacity adjustment to small seasonal changes in *PS*, which can, in turn, lead to negative improvements (as in Env#5).

We next focus our attention on scenarios where seasonal capacity adjustments provide significant improvements of larger than 1–2%. Specifically, these include Env#1, #2 and #4 (high *SEAS*, high *PS*) under all three demand strategies plus Env#6 (low Seas, PS-*PN* = 20–20%) under SDI. Figure 4 shows that implementing a more advanced demand strategy, such as SDI versus BL, can reinforce the benefits of seasonal capacity adjustments in environments with high demand uncertainty due to high probability of same-day patients and/or no-shows. This can be explained by the fact that demand strategies, such as SD and SDI, address only the demand variability of same-day patients and no-shows; and thus combining it with seasonal capacity adjustments address *both* demand and capacity variability. With less advanced demand strategies such as BL and SD, environments Env#2 and #6 with *PS*-*PN* = 20–20% may still suffer excessive residual volatility from walk-ins and/or no-shows, and thus realise much lesser benefit from capacity adjustments relative to SDI in Figure 4(ii).

In summary, we observe that *PS* and *SEAS* are the most critical factors for determining the success of capacity adjustments in appointment system design. In contrast, the cost ratio of doctor's to patients' time has a less definite influence on the capacity strategies. In environments with high seasonal variations and high probabilities of same-day patients and no-shows, combining same-day scheduling and no-show intervention with capacity adjustment offers the greatest benefits.

6. Conclusions

The main goal of this study is to investigate strategies for managing clinic variability in order to better match demand and capacity through refinements in appointment systems by implementing demand and/or capacity strategies. Demand strategies include same-day scheduling with or without intervention for no-shows. Same-day scheduling requires the clinic to ask same-day patients to call for appointments before arrivals, as opposed to letting them arrive as random walk-ins. No-show intervention requires the clinic to call advance-booked patients a day before their appointments and use cancelled slots for same-day demand. Finally, capacity strategies require that seasonal adjustments are made to the daily number of slots allocated between same-day and advance-booked patients. These demand and capacity strategies are illustrated over two different appointment rules, IBFI and Dome, and the resulting appointment systems are evaluated based on the expected total cost of the system, measured as a weighted sum of patients' wait times and doctor's idle-time and overtime.

Using simulation, we tested twelve appointment systems as different combinations of appointment rules, demand and capacity strategies, under eight environments and three cost ratios. Our results indicate that the choice of an appointment rule, which sets the template defining the combination of block size and appointment interval, is a major decision. The universal Dome rule developed by Cayirli et al. (2012), which is by design adjustable to specific characteristics of any clinic, always outperforms IBFI, and thus provides a solid foundation upon which more advanced demand and capacity strategies can be built. This affirms the universality of the Dome rule to be easily parameterised to perform well across a wider range of environments than tested originally. The second major decision to improve clinic performance is to reduce random walk-ins as much as possible through same-day scheduling. Extra, but smaller gains are achievable through implementing same-day scheduling with no-show intervention, a combined strategy that succeeds in reducing the demand variability further. Finally, capacity strategies help improve the system performance, albeit with diminishing benefits for the factor levels tested in our experiment.

An extended analysis is provided on the effects of different environmental factors on the improvements from different demand and capacity strategies. Demand strategies (ie, same-day scheduling and intervention for no-shows) are mainly affected by the probability of same-day demand and/or the probability of no-shows or cancellations, and are much less affected by demand seasonality. On the other hand, capacity strategy is mainly affected by the probability of same-day demand and demand seasonality, with some interfering effect by no-show probability. Cost ratio does affect the expected benefits from both the demand and capacity strategies, although its effect is not always easy to generalise across different environments. Finally, there are some interaction effects between the demand and capacity strategies, which indicate that maximum benefits occur when the most advanced demand strategy combining same-day scheduling and no-show intervention is implemented together with seasonal capacity adjustments for environments with high same-day demand and high seasonality.

In sum, our findings show that the healthcare managers have several levers to manage clinic variability and thus improve performance. This may require decision-makers to think beyond the traditional appointment rules, and adopt more invasive approaches for matching demand to capacity. Fine-tuning the appointment rules by adding open slots for same-day appointments and/or adjusting daily capacity for seasonal demand will naturally result in more complex appointment systems. Some of these approaches, like the intervention policy for no-shows, will also require extra efforts and resources in implementation. Therefore, when determining the best strategies, each clinic has to carefully evaluate the expected benefits and costs, given its own clinical environment. Future work may test new appointment systems under a wider set of environments, including patient and physician unpunctuality, heterogeneous service times, different no-show or walk-in rates for different patient classes, and patient's preferences. Multi-server and multi-phase systems could also be modelled to test the suggested appointment systems under more complex clinical environments.

Notes

1. An online tool for the Dome rule can be reached at http://www.appointmentschedulingtool.com/.
2. Variation or standard deviation of seasonal demand is a product of the seasonal *Cv* and probability of same-day patients *PS*.

Disclosure statement

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