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Optimizing outpatient appointment scheduling: Innovative strategies for enhanced efficiency in psychiatric clinics

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A B S T R A C T

Patient punctuality significantly impacts resource utilization and patient waiting times, among other quality indicators, within psychiatry clinics. In pursuit of service improvement, this study endeavors to develop effective appointment scheduling systems that optimally distribute patients' needs during clinical sessions, thereby enhancing resource utilization and patient satisfaction. In developing these scheduling rules, three patient-related uncertainties are considered: preference, availability, and punctuality. Various scheduling rules are evaluated based on their average total cost under different scenarios. The HSBGDM rules have emerged as a balanced approach for clinic operations, effectively managing physician time but occasionally leading to overtime variations. Increased patient delays often exacerbate physician idle times, particularly under IBVST and VBVST rules. Hybrid rules, such as the HSBGDM series, adapt well, improving patient wait times and managing unscheduled patients. However, scheduling systems like REPDM may prolong waits, potentially impacting patient satisfaction. Systems prioritizing new appointments can increase physician idle times due to unpredictability. While accommodating unscheduled patients enhances service quality, it may also cause disruptions. This study provides valuable insights into scheduling dynamics, assisting administrators in balancing efficiency, cost, and patient satisfaction.

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1. Introduction

Undoubtedly, the increasing popularity of outpatient procedures, driven by factors such as ease, comfort, and lower costs, has led to a surge in outpatient numbers (Berg et al., 2013). However, this growth presents new challenges for operational management in outpatient care, owing to the diverse patterns of patient behavior (Fan et al., 2019). Research by Song et al. (2015) indicates a staggering 60% rise in outpatient numbers, while the increase in physician numbers of lags at 25%. Projections by Srinivas and Ravindran (2020) suggest a shortfall of 35,000 to 44,000 physicians in the U.S. by 2025, underscoring the pressing need for support in meeting escalating healthcare demands. According to a survey conducted by Merritt Hawkins, a subsidiary of AMN Healthcare, outpatient clinics face an average delay of 24 days between appointment scheduling and service provision for patients, with medical personnel experiencing an average wait time of 23 minutes (Hawkins, 2017). This prolonged delay suggests an imminent risk of physician burnout, medical errors, decreased productivity, prolonged patient wait times, and appointment delays (Srinivas & Ravindran, 2018). Furthermore, idle resources during additional waiting times offer no contribution to outpatient clinic outputs, while patients' medical conditions remain unaddressed (Ir M et al., 2011; Kujala et al., 2006). Consequently, optimizing medical professionals' time usage and ensuring timely access to care emerge as crucial factors in elevating the standard of outpatient services (Srinivas & Ravindran, 2020). Patient unpunctuality is one aspect that affects patient waiting time and other clinic performance indicators, such as resource idle time and overtime (Aeenparast et al., 2021). Patient unpunctuality is a significant issue in many outpatient

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clinics worldwide (Okotie et al., 2008; Zhu et al., 2018). Patient unpunctuality is the interval between a patient's scheduled appointment and arrival time, suggesting they may arrive early or beyond time (Klassen & Yoogalingam, 2014).

The primary objectives of healthcare management initiatives are to reduce the average patient waiting times in outpatient clinics and to increase patient outcomes (Shehadeh et al., 2021). Appointment Scheduling (AS) systems can decrease patient wait times while improving the usage of expensive staff and facility medical resources. AS aims to provide an appointment system that enhances a particular quality standard in a healthcare application of scheduling tasks under uncertainty (Ala & Chen, 2022). Therefore, outpatient clinics need a successful AS to schedule patients and deliver high-quality care while managing limited resources. A well-designed AS enhances patient satisfaction and resource utilization and is essential for controlling future patient demand as it rises (Srinivas & Ravindran, 2020). One challenge related to developing a productive AS is scheduling patients who arrive earlier or later than their scheduled time (Klassen & Yoogalingam, 2014). Early arrivals could result in lengthier wait times and a congested waiting area. Such an occurrence can decrease patient service satisfaction and raise clinic operating expenses. Meanwhile, late arrivals could result in more "idle time" for the physician and lower clinic productivity (Guzek et al., 2015; Klassen & Yoogalingam, 2014; Taber et al., 2017; Wyatt et al., 2016; Zhu et al., 2018). Although all recent studies have shown significant improvements in AS by predicting patient no-show rates, none have considered the possibility of the patient’s unpunctuality rate. The scheduling of outpatient appointments can be greatly affected by the patient’s unpunctuality, which can impact clinic utilization, patient waiting time, and overtime costs. The study by Chen et al. (2023) utilized a simulation system to examine the effects of patient unpunctuality on appointment scheduling in a hospital's ultrasound department, comparing the preempt and waiting policies. The findings indicated that the preempt policy was more effective in scenarios with unpunctuality, and to minimize costs, the weight of the cost coefficient of both the radiological technician's idle time and patient waiting time must be equal, and the patient's inter-arrival time should be close to the average total time in the system (Chen et al., 2023). Another significant contribution to the literature is a comprehensive review of hospital multi-appointment scheduling problems (Marynissen & Demeulemeester, 2019). This study underscored the critical importance of timely care in preventing adverse health effects and enhancing patient satisfaction by reducing the frequency of hospital visits. The authors proposed a classification scheme to structure the existing body of literature, which revealed a notable increase in the popularity and momentum of multi-appointment scheduling problems in academic literature until the end of 2017. According to a study by Idigo et al. (2023), the impact of patient no-shows on appointment scheduling was conducted in the ultrasound unit of a Nigerian tertiary hospital. This cross-sectional study analyzed various factors, including the scheduling method, appointment delay time, appointment compliance rate, and no-show rate, using observation, patient records, and questionnaires. The study found that the single-block scheduling method was used, and the time interval between clinician request and examination appointment schedule was 12-14 days. Interestingly, the appointment compliance rate was 5.5, while the no-show rate was 4.5. Moreover, the poor state of ultrasound machines was identified as the highest contributing factor to patient delays, with a Kendall coefficient of concordance of 0.466. These findings are significant as they highlight the need for efficient planning of public hospital ultrasound units to enhance patient access and system efficiency (Idigo et al., 2023; Pazhooman et al., 2023). A novel study that addresses the challenge of resource scheduling in emergency departments in an uncertain environment was conducted by Liu et al. (2023). The authors proposed an innovative approach integrating Agent-Based Simulation (ABS) and Discrete Event Simulation (DES) and tested five combinations of strategies for scheduling the resources of the emergency department. The strategies tested were “FIFO + Random”, “FIFO + Centralized”, “Random + Centralized”, “Random + Random”, and “Autonomous”. The results indicated that the “FIFO + Centralized” strategy outperformed others in reducing the average duration of patients’ stay without hospitalization, saving 3.75% of the time. In contrast, the “Random + Centralized” strategy was most effective in reducing the average duration of patients’ stay with hospitalization, saving 0.57% of the time (Liu et al., 2023). These findings are significant as they provide valuable insights into optimizing resource scheduling in emergency departments, a critical factor in improving patient outcomes and system efficiency. Another study of interest focused on determining the optimal queuing system capacity based on changes in effective parameters, followed by a sensitivity analysis (Abdoli et al., 2023; White & Pike, 1964). The authors analyzed the total cost in public and private centers, accounting for patient waiting, rejection, and physician idle time. Specifically, the total cost in the public center comprised the costs of patient waiting time and rejection. In contrast, the private center included the costs of physician idle time in addition to the public center costs. A comparison of the results for public and private centers to reach a final assessment. This study is critical as it comprehensively analyzes the costs associated with different healthcare settings and offers valuable insights for optimizing queuing system capacity to minimize total costs. The study by Kanoun et al. (2023) proposed a novel two-fold multi-objective mixed integer linear program to minimize both patients’ total waiting and flow time and doctors' workload variations, considering patients, doctors, and machines simultaneously.

The efficacy of advanced scheduling methodologies in healthcare settings is demonstrated through various real case studies. In Tunisia, a study focusing on diabetic retinopathy patients showcased the practicality of implementing scheduling programs with time constraints. Kanoun et al. (2023) found that a program employing a specific time limit, based on its second formulation, offered the most optimal solution in terms of total flow time for patients. In another study by Dehghanimohammadabadi et al. (2023), a Multi-Objective Patient Appointment Scheduling (MO-PASS) framework was introduced to enhance clinic operations and improve the quality of care provided. This framework, incorporating optimization, data exchange, and simulation modules, was tested in a breast cancer clinic. Results indicated its superiority over existing heuristic benchmarks in minimizing total service time and maximizing the number of admitted patients without any overtime, demonstrating its practicality and feasibility for implementation. Furthermore, Jover et al. (2023) developed a two-stage scheduling model tailored for MRI scans, considering various uncertainties such as unpunctual patients, no-show patients, unscheduled arrivals, and different patient types. Their findings indicated that the model outperformed ad hoc scheduling practices by generating lower objective function values. This illustrates the model's effectiveness in optimizing limited healthcare resources and accommodating patients more efficiently. These real case studies underscore the significance of employing advanced scheduling methodologies in healthcare systems to improve operational efficiency, resource utilization, and patient satisfaction.

The primary objective of this paper is to develop a novel AS in a psychiatric clinic to schedule patients by considering their unpunctuality status to minimize the total cost of the clinic as well as patient waiting time, resource idle time/overtime, and number of patients without appointments. The structure of this paper is as follows: Section 2 presents the materials and methods used in this paper. Section 3 highlights the results, and Section 4 describes the conclusion.

2. Materials and Methods

2.1 Problem Description

We examine a single-stage psychiatric clinic that exclusively admits patients by appointment. A predetermined number of doctors in this clinic provide medical care solely to patients assigned to them. During discussions with the facility's supervisors, it became apparent that patient unpunctuality poses a significant challenge. The duration of appointment slots may either be continuous or vary depending on the patient's status (whether they are new or returning for follow-up care). Operational hours at the hospital, spanning from 8 a.m. to 5 p.m., are typically segmented into smaller time slots.

Additionally, the scheduling manager exercises discretion in accepting or rejecting each appointment request received on any given day. The number of patients allocated per slot adheres to established guidelines on overbooking policies, and our research endeavors to explore methods to potentially increase patient allocation within these slots. Furthermore, this clinic does not accommodate walk-in patients or experience instances of patient no-shows. Servers are expected to be utilized for administrative tasks, such as updating electronic health records (EHR), when not engaged in patient care. These administrative times are not factored into the evaluation of the Appointment Scheduling (AS) system. Additionally, the selected server may manage patient services for either shorter or longer durations than originally anticipated.

The assumptions underlying the simulated scheduling rules are outlined as follows:

- Each workday (8 a.m. to 5 p.m.) has 16 half-hour slots.
- The clinic has two physicians.
- Based on the overbooking and double-booking policy, each simulation model considers 70 patients.
- Each simulation model uses 500 replications.
- Depending on the AS and the patient’s status, patient service time is either fixed at 30 minutes or between 15 to 30 minutes.
- For each slot, a patient’s availability is determined randomly and represented in a binary format, where “1” indicates available and “0” indicates unavailable.
- Each patient’s physician preference is determined randomly, ensuring every patient is assigned to a physician.
- According to a study by (Kasaie & Rajendran, 2023), the rate of patient unpunctuality is 71%.
- Each time slot allows for an overbooking of two to four patients.
- Patients are scheduled sequentially upon calling the clinic without bookings.
- Patients are scheduled according to availability and physician preference, with those not fitting any slot labeled as “unscheduled”.

2.2 Appointment Rules

The appointment rule comprises a set of guidelines derived from clinic data, such as the average waiting time for patients attending the clinic. These guidelines determine the duration of appointments for each slot, the number of patients to be scheduled in each slot, and the selection of slots available for patient scheduling. In this study, we employ four types of appointment rules, which are delineated as follows:

(1) Individual Block Fixed Service Time (IBFST) Rules: Patients are scheduled in discrete blocks, with the time between two patients set equal to their mean service times, typically 30 minutes. In essence, each patient is allocated a specific slot, and the duration of each slot remains consistent throughout the clinic session.

Current System: We utilize the existing Appointment Scheduling (AS) method employed at the clinic under study as a benchmark rule. In this rule, there is no provision for overbooking, and only one patient is scheduled in each slot.
2ATBEG: This scheduling system adopts a strategy of booking two patients in the initial slot to maximize early resource utilization and mitigate potential morning absences. Subsequent slots are designated for accommodating one patient each,

ensuring a consistent daily flow. With slot durations aligned to average patient service times, the system prioritizes efficient care delivery, enhances the patient experience, and minimizes wait times.

2ATEND: In this scheduling system, two patients are reserved for the final slot of the day to address potential delays and maintain physician engagement until the end of the clinic hours. Preceding slots are designed to accommodate one patient each, fostering a regular flow and shorter wait times overall. Slot durations are set based on average service durations, with the final double booking serving as a buffer against unforeseen cancellations, thereby optimizing patient satisfaction and resource utilization.

(2) Variable Block Fixed Service Time (VBFST) Rules: In these appointment rules, the number of scheduled patients in each slot varies dynamically, while the service time for each patient remains constant and equal to their mean service time, typically 30 minutes.

SR-3ATBEG: The SR-3ATBEG system initiates with three patients scheduled for the first slot, followed by two in the second slot, and one patient in each subsequent slot, all allotted the average service time. This strategy addresses uncertainties in patient arrival and sustains physician engagement throughout the day. By adjusting the number of patients per slot, potential delays are managed effectively, resulting in optimized wait times, enhanced resource utilization, and a well-balanced clinic schedule.

SR-4ATBEG: With the SR-4ATBEG system, the day starts with four patients scheduled in the initial slot, followed by a gradual decrease to three, then two, and finally one patient per slot, with each appointment set to the average service time. This approach manages early patient arrival uncertainties, ensuring a smooth and consistent flow while blending resource-intensive scheduling with predictable durations to enhance operational efficiency and the patient experience.

SL-3ATEND: The SL-3ATEND system arranges single appointments during the day, transitioning to two and three patients in the final two slots to accommodate late-day preferences and maintain physician engagement. Slot durations, aligned with average service times, ensure operational consistency and optimize end-of-day resources while meeting patient demands.

SL-4ATEND: This system begins with single-patient slots, gradually transitioning to increased patient intake as the day progresses, thereby optimizing resources and catering to late appointments. Consistent slot durations, matching average service times, provide a predictable and efficient patient-provider experience.

REPDM-3: Following a recurring intake pattern, the REPDM-3 system schedules three-patient slots at intervals, interspersed with two-patient buffers and single-patient slots for focused care. This structured approach optimizes resources and flexibility while offering a predictable three-two-one pattern, balancing service quality and patient preferences effectively.

REPDM-4: The REPDM-4 system employs a tiered intake approach, with four-patient slots strategically placed at critical times, alternating with three and two-patient buffers, and individual care slots. This rhythmic scheduling method ensures efficient resource allocation and tailored care delivery, adapting smoothly to diverse patient needs.

(3) Individual Block Variable Service Time (IBVST) Rules: In these appointment rules, each slot is consistently allocated to one patient, while the service time varies based on the patient's status. Specifically, the service time for new patients ranges from 15 to 20 minutes, while for follow-up patients, it ranges from 21 to 30 minutes.

LSBEG-1: This scheduling system prioritizes new patients by reserving 80% of the early slots for them. This approach acknowledges the additional time and attention often required for initial evaluations or paperwork. By accommodating new patients first, clinics can enhance patient satisfaction and potentially increase revenue due to the more extensive services typically involved in initial consultations.

LSBEG-2: In this model, 70% of the early slots are allocated to new patients, while ensuring timely follow-up slots. This system values both comprehensive initial consultations and the importance of subsequent visits. By organizing appointments in this manner, clinics can achieve operational efficiency and smooth appointment transitions, considering that follow-up visits are often more concise and focused.

LSBEG-3: The LSBEG-3 scheduling approach designates 60% of the initial slots for new patients, striking a balance between first-time and returning consultations. This setup, suitable for clinics with a well-balanced patient mix, facilitates efficient patient flow and prompt service. By dedicating a significant portion of the day to follow-ups, the system emphasizes the importance of consistent care and timely subsequent appointments in healthcare delivery.

HSBEG-1: The HSBEG-1 scheduling model reserves the first 20% of slots for follow-up patients, recognizing the potential variability in their consultation durations. This structure prevents potential disruptions to the day's flow caused by extended consultations. New patients, with shorter and more consistent durations, are scheduled later, ensuring a steady operational pace while emphasizing ongoing care and operational efficiency.

HSBEG-2: In this system, 30% of slots are allocated to follow-up patients, accommodating their potentially variable consultation lengths. This setup is particularly suitable for clinics with a significant number of returning patients. By balancing between follow-up and new patient appointments, the system ensures thorough care for returnees while providing a smooth process for new patients.

HSBEG-3: The HSBEG-3 scheduling system designates the first 40% of slots to follow-up patients, catering to clinics with a strong focus on returning patients. Acknowledging the varied consultation durations of follow-ups, this setup optimizes resource utilization and facilitates the transition to new patient slots. It underscores the clinic's commitment to ongoing care, balancing the needs of a substantial returning clientele with those of new patients.

(4) Variable Block Variable Service Time (VBVST) Rules: These rules combine the *IBVSTI* with the *REPDM-4* rule.

LSBGDM-1: Combining the REPDM-4 slot pattern with an 80% reservation for new patients, akin to LSBEG-1, the LSBGDM-1 model suits clinics with a high volume of new patient intakes. Especially effective for clinics offering specialized services or targeting new clientele, it emphasizes thorough initial consultations, ensuring operational efficiency and impactful first encounters.

LSBGDM-2: Integrating the REPDM-4 slot arrangement with a 70% reservation for newcomers, echoing the LSBEG-2 approach, this model is well-suited for clinics balancing new and returning patients. Emphasizing the introduction of new patients and the importance of follow-up care, it serves clinics aiming for a balanced patient care experience.

LSBGDM-3: Fusing the REPDM-4 slot blueprint with a 60% emphasis on newcomers, reflecting notable consideration for returning patients, the LSBGDM-3 model is tailored for environments like chronic care centers where follow-ups are frequent. This approach ensures both the integration of new patients and sustained care for returning patients, optimizing timely and thorough consultations.

HSBGDM-1: Blending the REPDM-4 slot pattern with HSBEG-1’s focus on early follow-up consultations, dedicating a mere 20% of slots to newcomers, this model prioritizes sustained care. Particularly suitable for clinics where returning patients might require extended consultations, it underscores the importance of treatment continuity while accommodating a controlled number of new patients.

HSBGDM-2: Combining the REPDM-4 slot pattern with HSBEG-2’s preference for early follow-up appointments, with only 30% of slots allocated to newcomers, this model caters to clinics with a balanced influx of new and returning patients. Offering a structured yet adaptable scheduling approach, it ensures efficient resource allocation.

HSBGDM-3: Merging the REPDM-4 slot pattern with HSBEG-3’s early emphasis on follow-ups, setting aside 40% of slots for newcomers, this model prioritizes returning patients while accommodating a significant number of new consultations. Designed for clinics valuing continuous care, it efficiently manages patient intake while ensuring a substantial portion of the day is dedicated to new patients.

2.3 Procedures of the Simulation Models

Simulation models are constructed to develop the Appointment Scheduling (AS) system and calculate the corresponding weighted score for each. Initially, a simulation of the scheduling procedure is conducted, wherein patients sequentially request appointments and are assigned timeslots based on the designated scheduling rule. Patients are categorized based on their preference for either physician 1 or physician 2. For patients without a specific preference, assignment to a resource is randomized. Subsequently, patient availability is considered, wherein each patient can indicate their availability for one or more slots on the designated day. The overbooking policy remains consistent across all AS systems, despite variations in the number of overbooked patients for each. In this policy, the next scheduled patient for a given slot may arrive either "early" or "on time" if the preceding scheduled patient for that slot arrives "late." However, if the prior scheduled patient arrives "early" or "on time," the following patient may also arrive "late." This overbooking strategy aims to mitigate physician overtime, as consecutive "late" arrivals for a slot would result in increased overtime.

Below outlines the creation of simulation models for a specific scheduling horizon, along with algorithms detailing the schedule construction and computation of schedule outcomes.

Step 1: Choosing one of the proposed scheduling rules

Step 2: A patient calls for an appointment

Step 3: Check the patient’s unpunctuality status based on the results of the machine-learning algorithm's prediction

Step 4: Check the patient preference for physicians. If Yes, then go to Step 5. Else, go to Step 6

Step 5: Select the first slot

Step 6: Assign the patients without any preference to the first available physician and go to Step 5

Step 7: Check the patient availability for the selected slot. If Yes, then go to Step 8. Else, go to Step 11

Step 8: Check if the selected slot is empty. If Yes, then go to Step 9. Else, go to Step 10

Step 9: Schedule the patient in the selected slot and go to Step 14

Step 10: Check the possibility of scheduling the patient in the selected slot based on the overbooking policy. If Yes, then go to Step 9. Else, go to Step 11

Step 11: Check if it is the last slot under consideration. If Yes, then go to Step 12. Else, go to Step 13

Step 12: The patient cannot be scheduled, and go to Step 14

Step 13: **Select** the next slot and go to Step 7

Step 14: Check if the patient under consideration is the last. If Yes, then go to Step 16. Else, go to Step 15

Step 15: Wait for the next patient call, then go to Step 2

Step 16: STOP. The simulation model is completed.

Algorithm 1. Procedure for schedule construction

```
1   Procedure: set an initial feasible assignment
2     for p=1 to the final patient
3       for s=1 to the final slot
4.        If patient p is not assigned yet and is also available in the time slot s, then:
5           If patient p has a preferred physician, then:
6           find the patient p's preferred physician f
7           If no patient is assigned to the physician f, then assign p to him
8           Else if physician f has slot capacity, then:
9               Find previous patients assigned to the physician f and their level of lateness
10            If the last previous patient is late, then:
11                Don't assign the patient p to the physician f and go to step 3
12            End if
13          End if
14            Else assign the patient p to the physician f
15          Else if the patient p does not have a preferred physician, then:
16            for f=1 to the final physician
17              If physician f has capacity in the slot s
18                Find all previously assigned patients to the physician f
19                If all previous patients are not late, then:
20                    assign the patient p to the physician f
21                    Break for and go to line 2
22                End if
23              End if
24            End for
25            for f=1 to the final physician
26              If the physician has capacity in slot s
27                Find all previously assigned patients
28                If the last previous patient is late and f=last physician, then:
29                  Break for and go to line 2
30                Else
31                  assign the patient p to the physician f
32                End if
33              End if
34            End for
35          End if
36        End if
37      End for
38    End for
39  End Procedure
```

Algorithm 2. Procedure for computing schedule outcome

```
1   Procedure: schedule patients according to determined assignment and calculate PI, PO, and WT
2   Set patient scheduled service time (SSST)=patient scheduled arrival time (SAT)
3   Set patient actual service start time (ASST)=patient actual arrival time (AAT)
4.  Set patient scheduled service end time (SSET)=patient scheduled service start time (SSST)+patient service time (ST)
5   Set patient actual service end time (ASET)=patient scheduled service start time (ASST)+patient service time (ST)
6     for p=1 to the last patient
7       If the patient p is assigned to a physician
8         Find the patient p's physician and name it f
9         Find previously assigned patients to the physician f
10        Order previous patients with regard to their arrival times
11        Find the last patient and his/her ASET
12        If ASET of the current patient (p) is greater than ASET of the last patient (p'), then:
13          Set WT of the patient equal to zero and PI of the patient equal to ASST(p)-(ASET(p')
14        Else
15          Set PI of the patient equal to zero and WT of the patient equal to ASST(p')-ASET(p)
16      End if
17    End for
18    for p=1 to the last patient
19      PO=max(ASET(p)-SSET(p),0)
20    End for
21  End Procedure
```

2.4 Schedule Outcomes

The notations used in this paper are as follows.

2.4.1 Indices and Sets

P	Patients set
$p.p'$	Index for patients, $p.p' \in \{1.2. \dots . N\}$
S	Time slots set
s	Index for time slots, $s \in \{1.2. \dots . T\}$
F	Physicians set
f	Index for physicians, $f \in \{1.2. \dots . Phy\}$

2.4.2 Parameters

SL_Cap_s	Capacity for time slot s
PRF_{pf}	Binary parameter equal 1 if patient p has preference for physician f and equal zero if otherwise
SAT_p	Scheduled arrival time for patient p
AAT_p	Actual arrival time for patient p
AV_{ps}	Binary parameter equal 1 if patient p is available in time slot s and equal zero if otherwise
ST_p	Service time for patient p
WI	Weight index for each objective
$lateness_p$	Lateness grade of patient p which equals to 1 if he/she is early, equals to 2 if he/she is on time, and equals to 3 if otherwise.
M	Big M Parameter

2.4.3 Decision Variables

AS_{psf}	Binary assignment variable equal 1 if patient p is assigned to time slot s and physician f and equal zero if otherwise
ASF_{pf}	Binary assignment variable equal 1 if patient p is assigned to physician f and equal zero if otherwise
TP_{fs}	Total patients assigned to physician f in time slot s
TPS_f	Total patients assigned to physician f
NP_p	Binary assignment variable equal 1 if patient p is not assigned at all and equal zero if otherwise
$TPSL_s$	Total patients assigned to time slot s to any physician
$SSST_p$	Scheduled service start time for patient p
$ASST_p$	Actual service start time for patient p
$SSET_p$	Scheduled service end time for patient p
$ASET_p$	Actual service end for patient p
WT_p	Average waiting time for patient p
PI_f	Average idle time for physician f
PO_f	Average overtime for physician f
Z	Aggregate objective function

2.4.4 Mathematical Formulation

The primary goal of the objective function (1) is to reduce the weighted average of excessive patient waiting times, resource idle times, resource overtime, and unscheduled patient appointments.

$$min\ Z = \sum_{f} WI_1 . PI_f + WI_2 . PO_f + \sum_{p} WI_3 . WT_p + WI_4 . NP_p \tag{1}$$

Constraint (2) determines the total number of patients assigned to a physician within a time slot. Constraint (3) indicates the total number of patients assigned to each physician in the entire scheduling horizon. Constraint (4) calculates the total number of scheduled patients.

$$TP_{fs} = \sum_{p} AS_{psf} \qquad \forall s.f \tag{2}$$

$$TPS_f = \sum_s TP_{fs} \qquad \forall f \qquad (3)$$

$$1 - NP_p = \sum_{s,f} AS_{psf} \qquad \forall p \qquad (4)$$

Also, constraint (5) calculates the total number of assigned patients within a time slot for each physician.

$$TPSL_s = \sum_{p,f} AS_{psf} \qquad \forall s \qquad (5)$$

Constraint (6) sets the lower limit for the scheduled start time of a patient equal to the predetermined appointment time for that patient. Constraint (7) indicates that the start time of each scheduled patient should be after the visit of the last patient by the same physician.

$$SSST_p \geq SAT_p \qquad \forall p \qquad (6)$$

$$SSST_p \geq SSET_{p'} - M.(2 - ASF_{pf} - ASF_{p'f}) \qquad \forall f.p.p'.p \geq p' + 1 \qquad (7)$$

Constraint (8) specifies the lower limit for the actual start of service for each patient. Constraint (9) indicates that the actual start time of each patient's visit should be after the visit of the last patient by the same physician.

$$ASST_p \geq AAT_p \qquad \forall p \qquad (8)$$

$$ASST_p \geq ASET_{p'} - M.(2 - ASF_{pf} - ASF_{p'f}) \qquad \forall f.p.p'.p \geq p' + 1 \qquad (9)$$

Constraint (10) and (11) calculate the scheduled and actual end time of service for each patient, respectively.

$$SSET_p = SSST_p + ST_p \qquad \forall p \qquad (10)$$

$$ASET_p = ASST_p + ST_p \qquad \forall p \qquad (11)$$

Constraint (12) calculates the waiting time for each patient. Also, Constraints (13) and (14) indicate the idle time and overtime for each physician created by each patient.

$$WT_p \geq \min_{p'|p \geq p'+1} (ASET_{p'} - AAT_p) - M.(2 - ASF_{pf} - ASF_{p'f}) \qquad \forall f.p.p' \qquad (12)$$

$$PI_f \geq \min_{p'|p \geq p'+1} (ASST_p - ASET_{p'}) - M.(2 - ASF_{pf} - ASF_{p'f}) \qquad \forall f.p.p' \qquad (13)$$

$$PO_f \geq ASET_{70} - SSET_{70} \qquad \forall f \qquad (14)$$

Constraints (15) and (16) consider the scheduled and actual service start time equal to the scheduled and actual arrival time for the first patient, respectively.

$$SSST_1 = SAT_1 \qquad (15)$$

$$ASST_1 = AAT_1 \qquad (16)$$

According to constraint (17) assigning a patient to a time slot is only possible if the patient is available in the time slot. Constraint (18) considers the number of assigned patients to each time slot less than or equal to the upper capacity limit of that slot. Also, constraint (19) ensures the assigning of each patient only to the preferred physician. Constraint (20) specifies which physician belongs to each patient. Constraint (21) prevents the scheduling of two late patients in a row for a physician.

$$\sum_f AS_{psf} \leq AV_{ps} \qquad \forall p.s \qquad (17)$$

$$TP_{fs} \leq SL\_Cap_s \qquad \forall f.s \qquad (18)$$

$$AS_{psf} \leq PRF_{pf} \qquad \forall p.s.f \qquad (19)$$

$$\sum_s AS_{psf} = ASF_{pf} \qquad \forall p.f \qquad (20)$$

$$AS_{psf} + AS_{p'sf} \leq 7 - lateness_p - lateness_{p'} \qquad \forall p.p'.s.f.p \geq p' + 1 \qquad (21)$$

Constraints (22) to (24) are used to guarantee the decision variables' non-negativity and binary limits.

$$AS_{psf}.ASF_{pf}.NP_p \in \{0.1\} \qquad (22)$$

$$TP_{fs}.TPF_f.TPSL_s \in Int \qquad (23)$$

$$SSST_p.ASST_p.SSET_p.ASET_p.WT_p.PI_f.PO_f \geq 0 \qquad (24)$$

2.4.5 Evaluation of the Scheduling Rules

The main goals of the scheduling systems are to enhance patient satisfaction and resource utilization. In this paper, we use the average waiting time of patients (WT_p) and the average number of patients who could not make an appointment for a given day (NP_p) as metrics to gauge patient satisfaction. Likewise, the average idle time of physicians (PI_f) and average overtime of physicians (PO_f) are utilized as measured to determine resource utilization. To assess the effectiveness of the scheduling systems, the performance metrics are integrated with appropriate weights (WI). According to a study by (Srinivas & Ravindran, 2018), a total cost method is used to obtain the associated weights. In this method, authors used the median salary of the physicians and patients in the city where the clinic is located. However, this study uses a weight score system with four different scenarios. This decision is made to mitigate the problems regarding finding the cost of unscheduled patients. Table 1 shows detailed information regarding each scenario and their associated weights.

Table 1
Associated weights for each scenario

Scenarios	WI_1	WI_2	WI_3	WI_4
		PI Scenario		
PI (Base)	1	1.5	2	1
PI 2	1.25	1.5	2	1
PI 3	1.5	1.5	2	1
PI 4	1.75	1.5	2	1
PI 5	2	1.5	2	1
		PO Scenario		
PO 1 (Base)	1	1.5	2	1
PO 2	1	1.75	2	1
PO 3	1	2	2	1
		WT Scenario		
WT 1	1	1.5	1	1
WT 2	1	1.5	1.25	1
WT 3	1	1.5	1.5	1
WT 4	1	1.5	1.75	1
WT 5 (Base)	1	1.5	2	1
		NOAPP Scenario		
NOAPP 1 (Base)	1	1.5	2	1
NOAPP 2	1	1.5	2	2

3. Results and Discussion

3.1 Analysis of the Physician Idle Time

Fig. 1 shows the bar chart plot of the average physician idle time for various AS. The results demonstrate a substantial difference between the current system and all proposed AS ($p - value = 0$). Idle time refers to when no work is being done, which can lead to reduced productivity and efficiency. Therefore, minimizing idle time is an essential goal for scheduling.

The findings indicate that the current scheduling system exhibits an idle time of 13.67 minutes. Among the IBFST (Inter-Block Fixed Slot Time) rules, the 2ATEND rule demonstrates the lowest idle time at 14.37 minutes, followed by 2ATBEG with 15 minutes. Within the VBFST (Variable Block Fixed Slot Time) rules, SL-3ATEND exhibits the least idle time at 16.01 minutes, while SR-3ATBEG follows with 17.37 minutes. Regarding the IBVST (Inter-Block Variable Slot Time) rules, HSBEG-1 shows the highest idle time at 32.1 minutes, with HSBEG-2 following closely at 36.22 minutes. Conversely, within the VBVST (Variable Block Variable Slot Time) rules, HSBGDM-1 displays the lowest idle time at 12.36 minutes, with HSBGDM-2 trailing at 15.2 minutes. These results suggest that the VBVST rules are more effective in minimizing idle time, as they demonstrate the lowest idle times across the examined scenarios.

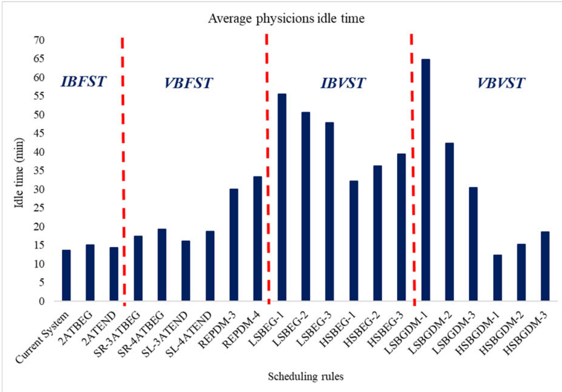


Fig. 1. The bar chart of the average physician's idle time

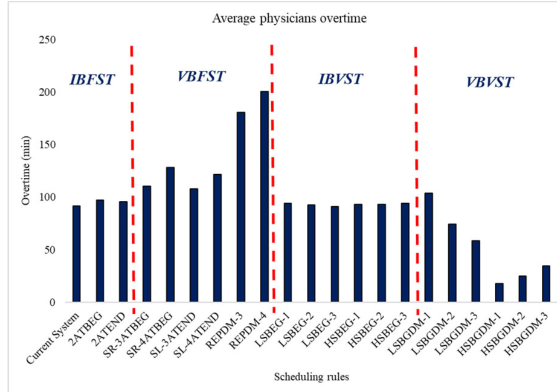


Fig. 2. The bar chart of the average physician overtime

3.2 Analysis of the Physician Overtime

The bar chart plot of the typical physician overtime for different AS is shown in Fig. 2. The findings show that all proposed AS and the current system differ significantly ($p - value = 0$). Overtime is time spent working past usual business hours, which can raise medical expenditures and lower employee satisfaction. As a result, reducing overtime is a crucial objective for scheduling. The analysis reveals that the current scheduling system experiences an overtime of 91.7 minutes. Among the IBFST (Inter-Block Fixed Slot Time) rules, 2ATBEG demonstrates the highest overtime at 97.15 minutes, followed closely by 2ATEND with 95.52 minutes. Within the VBFST (Variable Block Fixed Slot Time) rules, REPDM-4 exhibits the highest overtime at 200.78 minutes, with SR-4ATBEG following at 128.2 minutes. For the IBVST (Inter-Block Variable Slot Time) rules, LSBEG-1 displays the most pronounced increase in overtime at 94.05 minutes, closely trailed by HSBEG-1 at 92.95 minutes. Similarly, within the VBVST (Variable Block Variable Slot Time) rules, LSBGDM-1 demonstrates the highest overtime at 103.92 minutes, with LSBGDM-2 following at 74.35 minutes. It is noteworthy that no significant differences are observed in physician overtime among individual block rules (i.e., IBFST and IBVST rules). Overall, the findings suggest that the VBVST rules are more effective in minimizing overtime compared to other scheduling rules, as they exhibit the lowest overtime. Particularly, HSBGDM-1 showcases the lowest overtime at 17.77 minutes, followed by HSBGDM-2 with 24.75 minutes.

3.3 Analysis of the Patient Waiting Time

The average patient waiting times for different AS are displayed in Fig. 3. The findings show a significant difference between the present and alternative systems, $p - value = 0$. The time patients must wait before receiving treatment or services in the medical field is known as the patient waiting time. To deliver effective and high-quality medical care, patient waiting times must be minimal.

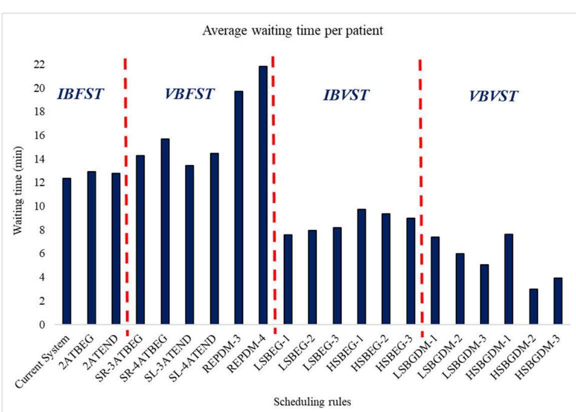


Fig. 3. The bar chart of the average patient waiting time

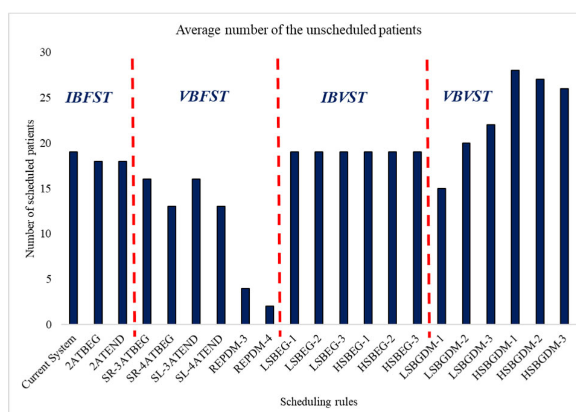


Fig. 4. The bar chart of the average number of unscheduled patients

The results show that within the IBVST rules, LSBEG-1 and LSBEG-2 are the most effective rules in reducing the patient waiting time at 7.55 minutes and 7.94 minutes, respectively. Within the VBVST rules, LSBGDM-3 and HSBGDM-2 are the most effective rules in reducing the patient waiting time to 5.02 minutes and 2.99 minutes, respectively. Overall, the VBVST rules have the lowest patient waiting time compared to other AS, indicating that these rules could be more effective in reducing the patient waiting time in the psychiatric clinic.

3.4 Analysis of the Number of Unscheduled Patients

Fig. 4 shows the bar chart plot of the average number of unscheduled patients for various AS. The results demonstrate a substantial difference between the current system, and all proposed AS ($p - value\ < 0.0001$). The analysis indicates that the current system, along with 2ATBEG and 2ATEND under IBFST rules, and all AS under IBVST rules, exhibit similar numbers of unscheduled patients. In contrast, the VBFST rules demonstrate lower numbers of unscheduled patients compared to the IBFST rules. Specifically, REPDM-3 and REPDM-4 rules showcase the lowest numbers of patients without appointments, with 4 and 2, respectively, followed by SR-4ATBEG and SL-4ATEND with 13 unscheduled patients. Within the VBVST rules, LSBGDM-1 displays the lowest number of patients with no appointment at 15, while HSBGDM-1 exhibits the highest number at 28. Overall, the VBFST rules emerge as having the lowest number of unscheduled patients among all scheduling rules.

3.5 Analysis of the Average Total Cost

3.5.1 PI Scenario

Fig. 5 displays the average total cost variations for different physician idle time weights across scenarios. The data reveals a marked distinction between the cases for PI and all proposed AS ($p - value = 0$). Using the robustness metric (difference between max and min total costs) is a novel way to evaluate the performance of the scheduling rule under different scenarios. A smaller robustness value indicates that the scheduling rule is more consistent across different unpunctuality rates.

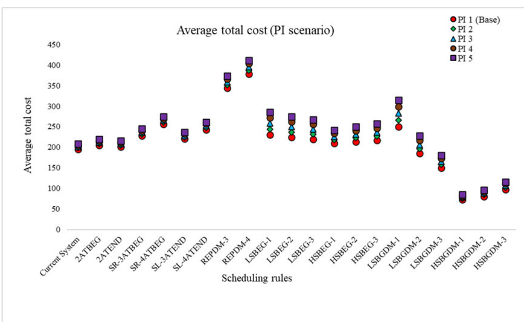


Fig. 5. The plot of the average total cost for each scheduling rule (PI scenario)

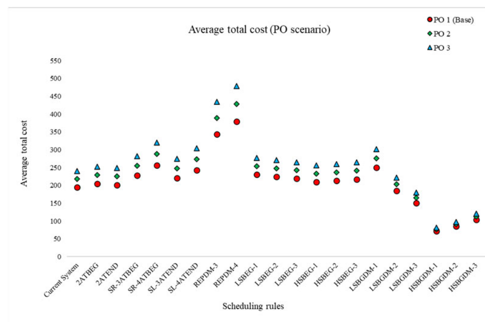


Fig. 6. The plot of the average total cost for each scheduling rule (PO scenario)

The findings reveal that various scheduling rules have distinct impacts on the total cost. Notably, 2ATBEG and 2ATEND exhibit smaller differences in cost between scenarios compared to others, suggesting greater robustness and less sensitivity to scenario changes. Conversely, LSBGDM-1 and LSBGDM-2 display higher differences in cost between scenarios, indicating greater sensitivity to scenario variations. Fig. 5 illustrates that VBVST rules are more effective in minimizing the total cost. Among these rules, HSBGDM-1 consistently demonstrates the lowest total cost across all scenarios, followed by HSBGDM-2 and HSBGDM-3. This underscores the efficacy of VBVST rules, particularly HSBGDM variants, in optimizing the total cost across different scenarios.

3.5.2 PO Scenario

Fig. 6 shows the average total cost for different weights associated with the physician overtime through various scenarios. The results demonstrate a significant difference between the other cases for PO and all proposed AS ($p - value\ = 0$). Among all Appointment Scheduling (AS) systems, it is evident that REPDM-4 exhibits the highest cost, while HSBGDM-1 demonstrates the lowest cost, followed by HSBGDM-2 and HSBGDM-3. This suggests that REPDM-4 should be avoided due to its higher cost implications, while VBVST rules emerge as the most cost-effective option. Furthermore, certain scheduling rules, such as REPDM-3 and REPDM-4, exhibit a higher disparity in cost among scenarios compared to others. This indicates that these rules may be less robust and more sensitive to changes in the scenario, as they struggle to maintain consistent performance across different conditions. Conversely, VBVST rules showcase a relatively low disparity in cost among scenarios, highlighting their robustness and adaptability to varying conditions.

3.5.3 WT Scenario

Fig. 7 shows the average total cost for different weights associated with the patient waiting time through various scenarios. The results indicate a significant difference between the other cases for WT and all proposed AS ($p - value\ = 0$). VBFST rules have a higher total cost than the other scheduling rules, which shows they could be more reliable in reducing the cost. On the other hand, the VBVST rule acts better in minimizing the total cost. For example, the HSBGDM-2 rule minimizes the total cost to 85.57 units in scenario 5, while REPDM-4 under VBFST increases the total cost to 378.92 units. Regarding robustness, VBVST is more robust and less sensitive to scenario changes, which shows these rules are better under different scenarios than other scheduling rules.

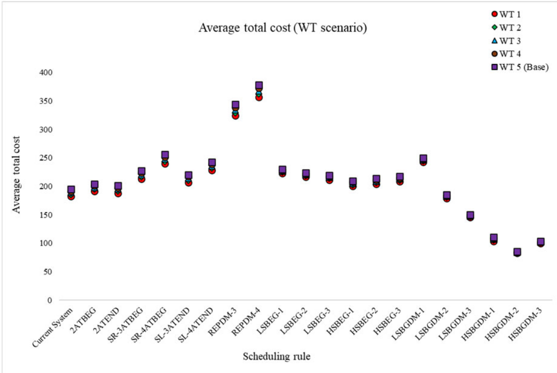


Fig. 7. The plot of the average total cost for each scheduling rule (WT scenario)

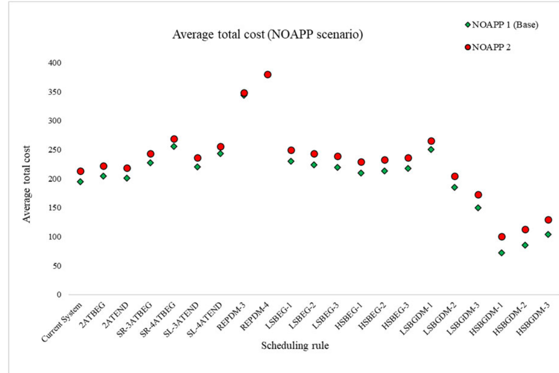


Fig. 8. The plot of the average total cost for each scheduling rule (NOAPP scenario)

3.5.4 NOAPP Scenario

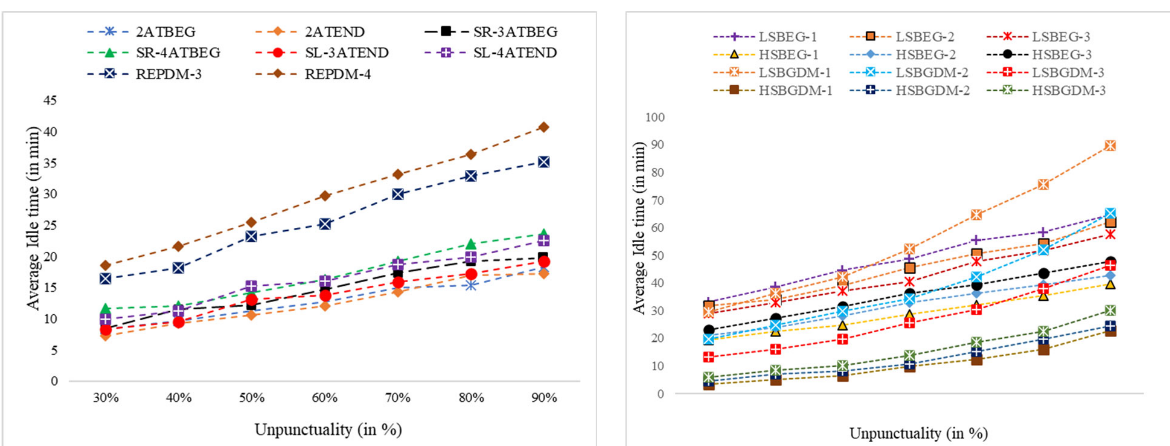
Fig. 8 shows the average total cost for different weights associated with unscheduled patients through various scenarios. The results show a significant difference between the other cases for NOAPP and all proposed AS ($p - value = 0$). Based on the results, it is evident that the total cost increases from the base scenario to scenario 2 for all scheduling rules. However, among the various rules, VBVST demonstrates the ability to minimize the total cost effectively. Although VBFST rules exhibit better robustness compared to other scheduling rules, VBVST rules still outperform them in terms of cost-effectiveness. This superiority is attributed to factors such as the minimum number of unscheduled patients observed in REPDM-3 and REPDM-4 rules under VBFST. Overall, VBVST rules prove to be the most cost-effective option among the different scheduling rules considered.

3.6 Sensitivity Analysis

In psychiatric clinics, the average rate of unpunctuality has been reported at 30% (Baggaley, 1993). Thus, this study investigates how varying rates of unpunctuality impact the scheduling system. The unpunctuality rates considered in this analysis range from 30% to 90%, with increments of 10%. For instance, a 40% unpunctuality rate signifies that, on average, 40% of patients do not arrive on time for their appointments.

3.6.1 Analysis of the Physician Idle Time

The average physician idle time across varying unpunctuality rates is illustrated in Fig. 9.



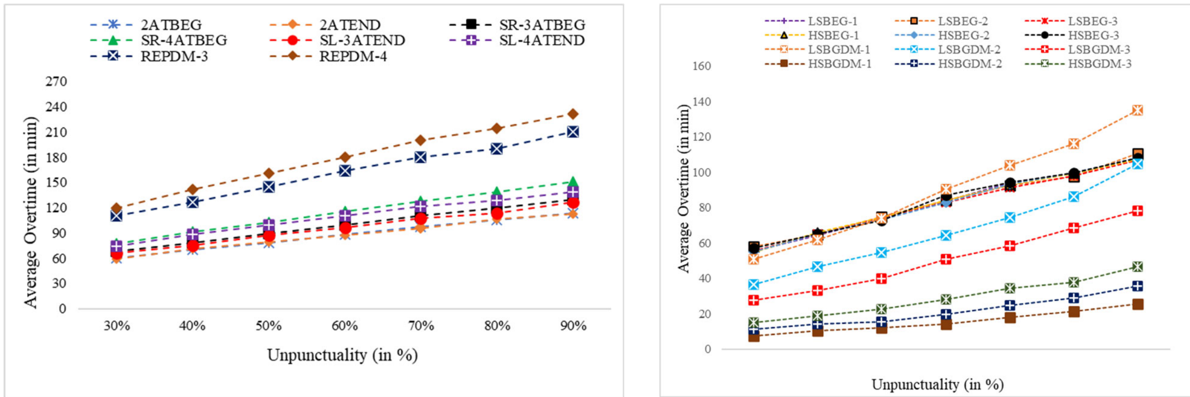
(a): IBFST and VBFST (b): IBVST and VBVST

Fig. 9. The plot of the average physician idle time for different unpunctuality rates

The results indicate that increasing the patient's unpunctuality rate generally results in increased physician idle time across all scheduling rules. A comparison of idle times between unpunctuality rates of 30% and 90% reveals a notable increase for all scheduling rules. This suggests that higher levels of patient unpunctuality may have adverse effects on physician productivity, as physicians may be required to wait longer between appointments, thereby reducing overall productivity. Moreover, the findings suggest that changes in physician idle time for IBVST and VBVST rules are more significant compared to IBFST and VBFST rules. Specifically, as the unpunctuality rate increases, the changes in idle time for LSBGDM-1 are more pronounced than for other appointment scheduling methods. However, Fig. 9(b) highlights that HSBGDM-1, HSBGDM-2, and HSBGDM-3 rules consistently outperform other scheduling rules across different unpunctuality rates, indicating their reliability and effectiveness under varying conditions.

3.6.2 Analysis of the Physician Overtime

The average physician overtime across different unpunctuality rates is depicted in Fig. 10.



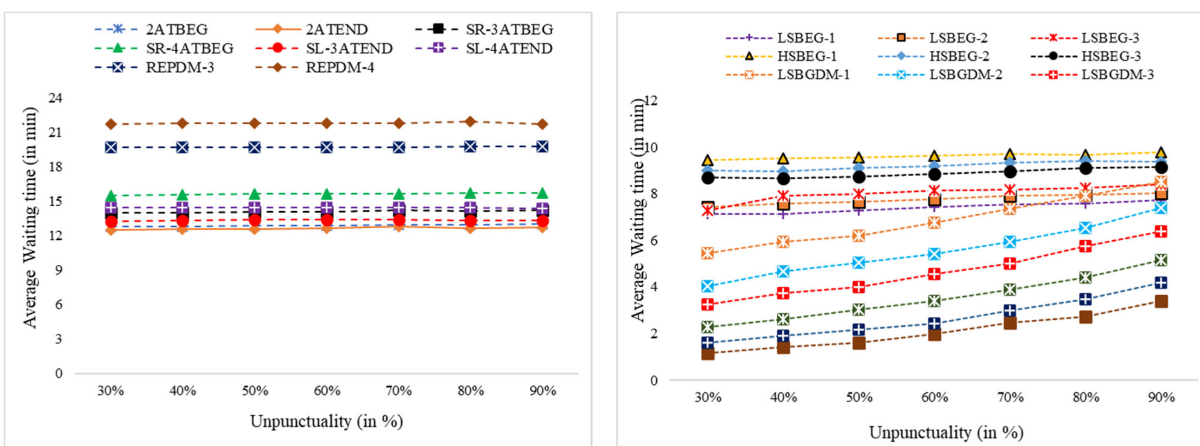
(a): IBFST and VBFST (b): IBVST and VBVST

Fig. 10. The plot of the average physician overtime for different unpunctuality rates

The analysis reveals that increasing patient unpunctuality generally leads to an increase in physician overtime across all scheduling rules. There is a noticeable uptick in overtime for all scheduling rules when transitioning from 30% to 90% unpunctuality rates. Figure 10(a) illustrates that within the IBFST and VBFST rules, REPDM-3 and REPDM-4 exhibit poorer performance compared to other AS rules in terms of physician overtime. However, IBVST and VBVST rules demonstrate better performance in terms of physician overtime across different unpunctuality rates. For instance, HSBGDM-1, HSBGDM-2, and HSBGDM-3 rules consistently exhibit the minimum amount of physician overtime among all scheduling rules, highlighting their superiority across different rates (Figure 10(b)).

3.6.3 Analysis of the Patient Waiting Time

Fig. 11 shows the average patient waiting time for different unpunctuality rates.



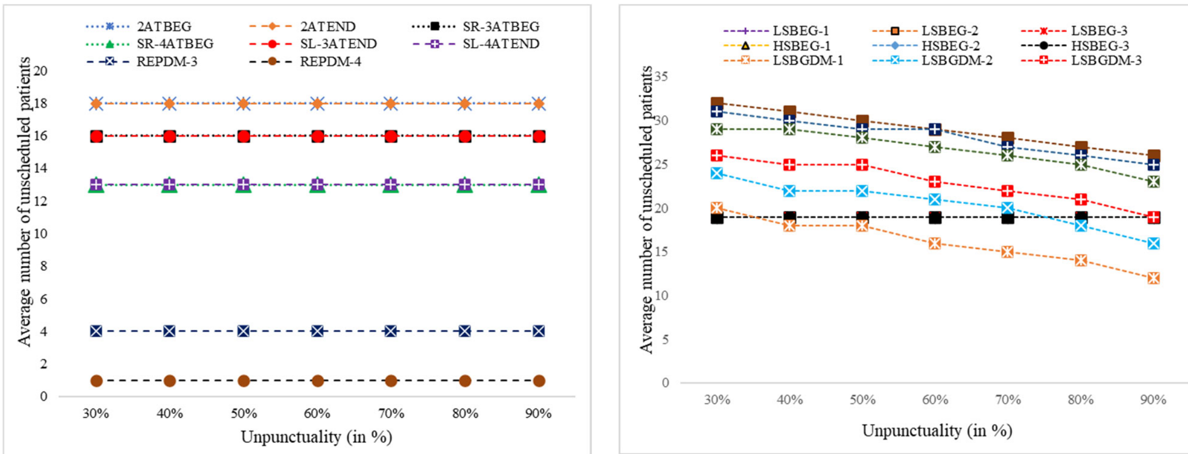
(a): IBFST and VBFST (b): IBVST and VBVST

Fig. 11. The plot of the average patient waiting time for different unpunctuality rates

The results depicted in Fig. 11(a) suggest that there is no significant relationship between patient waiting time and the unpunctuality rate. One possible explanation for this finding is that the service time for all patients remains fixed. Another explanation could be that the arrival times of some patients may offset those of others, resulting in no significant changes in waiting times. Furthermore, within the IBFST and VBFST rules, REPDM-3 and REPDM-4 exhibit poorer performance compared to other scheduling rules. On the other hand, Figure 11(b) reveals that patient waiting times remain relatively steady despite increasing rates of patient unpunctuality under IBVST rules. In contrast, VBVST rules demonstrate a positive correlation, indicating that as patient unpunctuality rates increase, waiting times for patients also increase. Moreover, the VST rules consistently outperform other methods in minimizing patient waiting time across various unpunctuality rates. For instance, HSBGDM-1 demonstrates the lowest waiting time per patient, followed by HSBGDM-2 and HSBGDM-3.

3.6.4 Analysis of the Unscheduled Patients

Fig. 12 shows the average number of unscheduled patients for different unpunctuality rates.



(a): IBFST and VBFST (b): IBVST and VBVST

Fig. 12. The plot of the average number of unscheduled patients for different unpunctuality rates

According to the results obtained in Fig. 12 (a), there is no meaningful relationship between the average number of patients without appointments and different unpunctuality rates. As the unpunctuality rate increases from 30% to 90%, the average number of unscheduled patients will stay the same. Also, within the IBFST and VBFST rules, REPDM-3 and REPDM-4 outperform compared to other scheduling rules. Based on Figure 12 (b) results, there is a negative correlation between the increment of the unpunctuality rate and the unscheduled patients for IBVST and VBVST rules.

3.7 Managerial Insights

Based on our analysis, we propose the following managerial suggestions:

Preference for HSBGDM-1: HSBGDM-1 consistently demonstrates cost-efficient results across all scenarios. It effectively manages metrics such as physician idle time, patient waiting time, overtime, and unscheduled patients, making it a top choice for comprehensive scheduling improvements.

Consider REPDM Models with Caution: REPDM models exhibit variability in total costs across different metrics. While they may excel in certain areas, such as minimizing unscheduled patients, they may incur higher costs in others, like overtime. Managers should weigh these trade-offs carefully when considering REPDM models.

Explore Hybrid Rules: Hybrid rules, particularly those in the HSBGDM series, often yield favorable total costs across diverse scenarios. This suggests that integrating features from various scheduling rules could be crucial for balancing service quality and cost efficiency.

Resilience to Unpunctuality Varies: Different scheduling rules respond differently to changes in unpunctuality rates. Some rules exhibit greater resilience, maintaining relatively stable performance metrics, while others show more significant fluctuations. Managers should consider the robustness of scheduling methods when addressing unpunctuality challenges.

Impact of Unpunctuality on Workflow: Increasing unpunctuality rates lead to noticeable increases in physician idle time, overtime, and patient waiting time. This disruption indicates the importance of managing unpunctuality to maintain efficient appointment flow and minimize waiting times for patients.

Flexibility of HSBGDM Series: The HSBGDM series, as hybrid rules, demonstrate flexibility and resilience across varying unpunctuality scenarios. Their ability to integrate features from different scheduling strategies makes them adaptable to changing clinic environments. Managers could leverage these hybrid rules for enhanced scheduling performance.

4. Discussion and Conclusion

The prevalence of patient unpunctuality poses significant challenges in mental health clinics, impacting various quality metrics such as resource utilization and patient waiting times. This chapter aimed to evaluate the effectiveness of new scheduling rules in addressing these challenges and optimizing clinic operations in a psychiatric setting. The key findings of this study are summarized below:

- HSBGDM-1 Emerges as a Balanced Approach: The HSBGDM-1 scheduling rule demonstrates effectiveness across multiple metrics, including physician idle time, patient waiting time, overtime, and unscheduled patients. Its balanced approach suggests efficient management of clinic operations.
- Trade-Offs Exist Across Metrics: While some rules show stability in certain metrics, they may exhibit variability in others. For example, while HSBGDM-1 maintains minimal fluctuations in physician idle time, it may experience more pronounced changes in overtime. Understanding these trade-offs is crucial in selecting the most suitable scheduling rule.
- Impact of Unpunctuality on Idle Time: Increasing rates of unpunctuality generally lead to higher physician idle times, particularly for IBVST and VBFST rules. This underscores the sensitivity of these rules to disruptions and emphasizes the need for effective patient management strategies.
- Hybrid Rules Offer Adaptability: Hybrid rules, especially within the HSBGDM series, show promise in managing patient waiting times and unscheduled patients. By integrating features from different scheduling strategies, they exhibit adaptability and versatility in clinic operations.
- Considerations for REPDM Methods: While REPDM scheduling methods provide structured approaches, they may result in longer patient waiting times, potentially impacting patient satisfaction. Administrators should weigh the benefits of operational consistency against the drawbacks of increased wait times.
- New Patient Prioritization and Idle Times: Scheduling systems prioritizing new patients tend to result in higher physician idle times compared to those prioritizing follow-up patients. This highlights the variability and unpredictability associated with new patient appointments.

These findings offer valuable insights for healthcare administrators and managers, helping them make informed decisions to optimize scheduling practices while balancing operational efficiency, cost-effectiveness, and patient satisfaction in mental health clinics.

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