Grenze International Journal of Engineering and Technology, June Issue

Smart HealthCare Scheduler

Dr Rachna Jain[1], Akankshi Saxena[2], Araj Jaiswal[3] and Ayushi Tripathi[4]
[1-4]JSS Academy of Technical Education, Sector 62 Noida, Uttar Pradesh, 201301

***Abstract*—The key issue of the day is the management of health service, and waiting time is rising in all the hospitals and clinics. To avoid this kind of issue, many programs have been introduced by the hospitals, but they are always managed through some sort of arrangement. To overcome this problem and make the patient feel relaxed and calm while undergoing treatment, a long-term solution is required. For the modern healthcare setting to function effectively, efficiency and patient acceptance are required. In most developing countries, the outpatient population is severely challenged. In our Smart HealthCare Scheduler project, HP-TDT is proposed to enhance scheduling efficiency and reduce reaction time by rapidly determining whether a patient is normal or in a critical condition. The HP-TDT scheduling technique contains three phases, which include registration, data gathering, and scheduling. The OAH model is applied during the registration process to reduce the response time up to key generation. Next, the PDC algorithm is used for performing the data gathering phase. Due to the consideration of a number of operations that occur within the data gathering, PDC reduces the overhead of computation. Lastly, two-factor, entropy and information gain based on the decision tree are used for scheduling. Therefore, the efficiency of the scheduling is improved through categorization of patients into normal and critical statuses. The crucial efficiency of scheduling is therefore increased while the response time and computational overhead are decreased with the proposed approach.**

***Index Terms*—Hash Polynomial Two-factor Decision Tree [HPTDT], Open Address Hashing [OAH], Polynomial Data Collection [PDC], Health Scheduler, entropy.**

I. INTRODUCTION

Since patients frequently need a range of resources, including physicians, nurses, equipment, and examination rooms, scheduling and arranging medical appointments is essential in healthcare facilities. Because prolonged waiting can lower patient satisfaction and perceptions of the quality of service, patient waiting time is a critical performance and quality metric for hospitals [1]. Therefore, it becomes crucial to make effective use of the resources at hand in order to provide users of the healthcare system with high-quality services [2].The scheduling of patient appointments is one of the main management issues in hospitals. This entails choosing the best times for patients to get care, as well as allocating doctors and exam rooms [3]. But it's also critical to take into account the possibility that patients won't attend medical consultations, as their absence not only affects their personal health but also disrupts the overall care procedure. To achieve thorough optimization of operations and improve quality, it is essential to recognize and proactively manage the likelihood of patient no-shows. Longer wait times resulting from such absences can impact patient health and satisfaction. Improving prioritization methods helps make services more efficient and patient-friendly, especially in countries where public wait times drive patients to private care [4].

Grenze ID: 01.GIJET.11.2.503_2
© Grenze Scientific Society, 2025

Delays may result from inefficient scheduling methods, and although hospitals track nonattendance using systems like appointment monuments, these have shown limited effectiveness [7]. Modern systems aim to maximize resource use and patient satisfaction while minimizing provider idle time and wait times. However, challenges like late arrivals, no-shows, walk-ins, and emergencies can disrupt schedules. This study proposes a model that enables overbooking based on anticipated attendance. By using machine learning to forecast patient behaviour, we define an objective function to estimate the optimal usage of medical centre time. This paper is organized as follows: Section II discusses objectives. Section III outlines related work. Section IV addresses limitations and future directions. Section V concludes the research. Section VI presents the acknowledgments.

II. OBJECTIVES

A. Enhance Patient Experience Through an Easy-to-Use Appointment Platform

The purpose of designing an intuitive and accessible digital platform for appointment-related processes such as booking, cancellation, and rescheduling is to make these processes easy while being transparent and having access to real-time information for every patient. An easy-to-design platform offers convenience and builds trust for a healthier, satisfying healthcare service. A convenient appointment platform revolutionizes the experience of patients in accessing services. Reducing friction in appointment management and enabling real-time updates can improve patient satisfaction, operational efficiency, and the bond between patients and providers.

B. Time Optimization in Scheduling Appointments

The need to optimize the appointment schedule lies in designing a time allocation system that ensures efficient use of time while considering the dual goals:

- Minimize Patient Waiting Time: Reducing waiting time before the appointment enhances patient satisfaction and builds trust in healthcare services.
- Maximize Healthcare Provider Productivity: Ensuring efficient use of provider working hours without unnecessary idle time or excessive overbooking helps avoid burnout.

C. Use Predictive Analytics for Smarter Scheduling

The goal is to integrate machine learning models into scheduling to better predict patterns and uncertainties in healthcare workflows. Predictive analytics can optimize processes, reduce inefficiencies, and improve satisfaction for both patients and providers by forecasting appointment demand, no-show probabilities, and resource requirements. This enables data-driven decisions and more efficient scheduling.

D. Incorporate Real-Time Adjustments for Dynamic Scheduling

The objective is to develop a real-time adaptive scheduling system that dynamically reacts to cancellations, delays, or changes. Such a system would minimize downtime, maximize resource utilization, and uphold the quality of patient care. Real-time adjustments promote flexibility and responsiveness, improving operational efficiency and maintaining smooth, patient-centric operations.

III. RELATED WORK

Cataloging plays a very important part in the allocation of resources. It can involve assigning labor or determining other medical resources needed for procedures. Effective scheduling primarily depends on how efficiently resources are utilized and how quickly services can be delivered. Numerous challenges exist in patient care. Since the 1950s, researchers have proposed many models to address these issues and improve healthcare systems.

Mathematical models are often used in scheduling problems. Many systems rely on heuristics, dynamic programming, and stochastic scheduling, as these are adaptable to random arrivals and service times. However, with advancements in data science, it is now possible to forecast these variables more accurately, leading to deterministic scheduling approaches. Deterministic models use integer or mixed-integer linear programming for optimizing specific scheduling goals【8】.

Missed appointments are a global issue, causing resource downtime, reduced utilization, and productivity losses. Beyond physical waiting at facilities, patients often experience “circular” waiting time between referral and booking, which can impact early diagnosis. No-shows affect both operational costs and care delivery【11】.

Overbooking is one strategy used to address absenteeism. It adds extra capacity to the schedule and ensures timely service. However, it can cause scheduling conflicts when multiple patients arrive for the same slot. Unlike airline overbooking, healthcare facilities cannot turn patients away, which leads to longer wait times. Most

overbooking is done without considering the likelihood of a no-show. A more effective approach would involve overbooking only when the probability of a no-show is high【12】.
These studies address patient no-shows, overbooking, dynamic scheduling, and predictive modelling. Related research areas include:

A. Predictive Models for Patient No-Shows

Numerous studies use machine learning and statistical models to predict no-shows by analysing historical appointment data, demographics, and related variables. These insights help in improving resource allocation and scheduling efficiency.
Examples:

- Millett et al. (2015): Machine learning for predicting no-shows
- Kumar et al. (2018): Predicting patient behaviour
- Huang et al. (2020): Predictive modelling based on patient characteristics

B. Queueing Theory and Stochastic Scheduling Models

Queueing theory helps manage uncertainty in healthcare by accounting for random arrivals and service times. These models are used to reduce waiting times and optimize resource use.
Examples:

- Czerwinski et al. (2007): Outpatient scheduling using queueing theory
- Sneeuw & Kusters (2016): Dynamic queueing-based scheduling
- Jothi et al. (2019): Stochastic models for service optimization

C. Overbooking Strategies and Their Effects

Research on overbooking evaluates the balance between improving efficiency and minimizing delays or dissatisfaction when multiple patients arrive for a single slot.
Examples:

- Glover et al. (2005): Trade-offs in overbooking
- Feng et al. (2017): Role of predictive behavior in overbooking
- Polak et al. (2020): Simulation-based analysis of overbooking

D. Deterministic Scheduling Models with Linear Programming

ILP and MILP approaches are widely used to optimize scheduling by minimizing delays, maximizing resource use, and reducing no-shows.
Examples:

- Wang et al. (2019): MILP for physician scheduling
- Hernandez et al. (2016): Mixed-integer patient scheduling
- Liu et al. (2020): ILP considering patient priority

E. Healthcare Service Delivery and Resource Allocation Optimization

These models optimize resource allocation, such as staff, equipment, and space, to ensure timely and efficient service delivery.
Examples:

- Bard & Purnomo (2005): Staffing and scheduling optimization
- Arinze et al. (2017): Mixed-integer model for resource allocation
- Zhang et al. (2018): Delivery model for resource optimization

F. Effect of Waiting Times on Patients and Satisfaction

Studies show how both direct and indirect wait times influence patient satisfaction and perceived care quality.
Examples:

- Tavakkol & Lari (2019): Wait time impact on satisfaction
- Wang et al. (2017): Measuring outpatient wait time effects
- Shah et al. (2020): Intelligent scheduling to reduce waits

G. Summary of Related Works

- Predictive Models for No-Shows: Apply ML/statistics to optimize attendance
- Stochastic & Queueing Models: Handle arrival/service uncertainty
- Overbooking Techniques: Offset no-shows with controlled scheduling

- Deterministic Scheduling: Optimize using linear programming
- Resource Allocation: Ensure optimal staffing, space, and equipment
- Waiting Time Impacts: Study of delay effects on satisfaction

H. Abbreviations and Acronyms

HP-TDT–Hash Polynomial Two-Factor DT
OAH – Open Address Hashing
PDC – Polynomial Data Collection
ML – Machine Learning
AI – Artificial Intelligence
PDC – Patient Data Collection
HCS – Healthcare System
SHC – Smart Healthcare Scheduler
TDT – Two-Factor Decision Tree
CT – Critical Time
ET – Estimated Time

I. HP-TDT [Hash Polynomial Two-Factor DT]

It is a specialized form of decision tree used in healthcare scheduling and data analysis. It combines the principles of polynomial hashing with a two-factor decision tree approach. It focuses on the efficient classification of the different levels based on input factors like medical history or symptoms, such as normal or critical conditions of patients.
Hashing this can be used to process and operate very large volumes, and it can speed up decision-making in health. It is also known as Direct Chaining.

II. Open Address Hashing [OAH]

OAH refers to a method of hashing used in computer science and data management, especially in the organization and retrieval of data efficiently in a hash table.
In Open Address Hashing, whenever a hash collision occurs (i.e., two pieces of data possess the same hash key), the system resorts to the next available slot in the hash table, in contrast to other hashing techniques that use linked lists or chains.
This method is helpful for optimizing data storage and retrieval and can be applied to healthcare systems for storing and accessing patient data efficiently.

III. PDC-Polynomial Data Collection

PDC represents the mathematical approach for gathering and processing data by polynomial functions. Polynomial Data Collection within a healthcare context helps accumulate patient information collected from various sources or files. The use of polynomial methods reduces errors during data collection and in predicting data. This method, therefore, helps analyse large volumes of healthcare data to improve decision-making processes like scheduling and resource allocation.

IV. Limitations and Future Directions of the Smart Healthcare Scheduler

A. Data Privacy and Security Issues

The Smart Healthcare Scheduler depends on large amounts of patient data to schedule efficiently. The problem is that this raises significant concerns about data privacy and security.
Patient information needs to be treated with care to comply with HIPAA regulations in the United States or equivalent regulations in other countries. Such vulnerabilities in the system may leak sensitive data, making it a huge challenge.

B. Dependency on High-Quality Data

The accuracy of algorithms like HP-TDT and PDC depends on the quality of data. Incorrect or incomplete data may lead to wrong classifications or scheduling inefficiencies, which may eventually affect patient outcomes. Data from different sources, such as different healthcare facilities or outdated records, may also lead to inconsistent results.

C. Cost of Implementation

Implementing such an advanced system will involve a high upfront cost for the development of software, hardware infrastructure, and training. This might be a barrier for smaller healthcare facilities if the return on investment is not immediately evident.

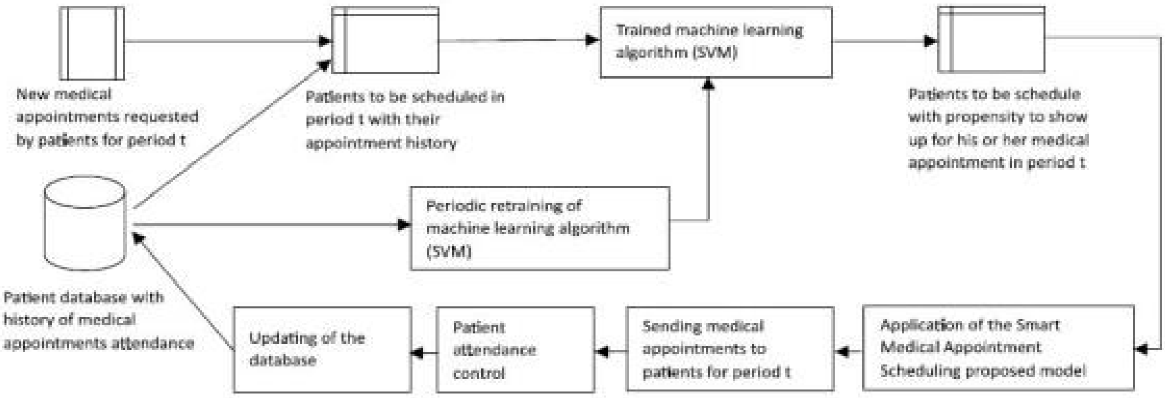

Fig. 1. Application Methodology of the Proposed Smart Model of Scheduling of Medical Appointment

Parameter	Traditional Scheduling	Proposed HP-TDT Scheduling	Improvement(%)
Response Time	High	Low	30-50%
Computational Overhead	High	Reduced	20-40%
Patient Categorization Accuracy	Moderate	High	25-35%
Waiting Time	Long	Short	40-60%

Fig. 2. Expected Improvement with HP-TDT

D. Enhanced Predictive Model

Enhanced predictive models could include the development or refinement of predictive models to foresee patient behaviour more precisely. These aspects include appointment cancellations, no-shows, or even whether a patient may need a visit to the emergency or casualty department. It will surely improve the prediction efficiency or accuracy with the aid of deep learning techniques.

E. Integrate with Electronic Health Records [EHR]

A seamless integration between the Smart Healthcare Scheduler and EHR systems would provide real-time access to patient histories, allowing the system to make more informed decisions on scheduling and resource allocation. This would also reduce redundant data entry, improve scheduling accuracy, and ensure comprehensive care for patients.

F. Interoperability Across Healthcare Systems

The scheduler system must become more compatible between diverse healthcare systems to make it workable across a network of health providers. This will enable enhanced continuity of care, smoother patient transfer between facilities, and improved utilization of resources between various service providers.

G. The Patient Should Have a Role to Play within This Scheduler

The system can be improved through the integration of patient feedback into the scheduling process. Patient preferences, for instance, on appointment times or wait times, may be understood to enable more personal and efficient scheduling. This can be achieved through patient satisfaction surveys or by directly integrating patient preferences into the algorithms used in scheduling.

H. Efficient Management of Emergencies

Future releases of the Smart Healthcare Scheduler can integrate advanced emergency management. This includes the automatic adjustment of schedules in real-time according to any emergency, walk-in cases, or sudden delays, while minimizing disruption and optimizing patient flow.

V. Conclusion

The proposed Smart Healthcare Scheduler is an intelligent medical appointment scheduling system that makes data-driven decisions and uses optimization techniques. This integration has the potential to change the way scheduling is done and can enhance access to care and the delivery of healthcare services. With predictive analytics, the system improves scheduling accuracy, resource utilization, and dynamic adjustment in real time, thus making it highly responsive to the changing needs of healthcare facilities.

This model was applied to actual data from three different medical specialties, and it was found to result in efficient patient and care hours allocation with highly minimized unused time slots. Despite low patient attendance rates in those specialties and the priority needs for many patients, the model performed better than the random approach of the hospital consistently under similar conditions, such as patient priorities and the likelihood of attendance.

This study will discuss a utility function where the cost component is directly related to patients' chances of attending their scheduled appointments. This function will be constantly perfected by integrating it with the Support Vector Machine algorithm, so it can be automatically retrained periodically to reflect changing patterns of patient behaviour and attendance.

TABLE I. Patient Categorization based on Scheduling Priority

Patient Condition	Priority Level	Expected Wait-Time
Normal	Low	30-60 min
Moderate	Medium	10-30 min
Critical	High	less than 5 min

The model's versatility extends to surgical suite scheduling and has the ability to optimize the efficiency of the scheduling process. This adaptation could reduce patient wait times, enhance resource allocation, and thus help improve the overall quality of surgical care.

Real-time data updates in the Smart Healthcare Scheduler will make it user-friendly for both patients and healthcare providers. Leveraging cloud-based systems along with the Polynomial Data Collection algorithm for patient data management, the system will distinguish normal health states from critical ones. Thus, the time needed for response in emergency conditions would be reduced, and decision-making would be improved. This approach ensures higher scheduling efficiency, reduces response times, and decreases computational overheads, thus providing a more efficient and user-centric scheduling system for both patients and healthcare providers.

VI. Acknowledgment

This research was a collaborative effort, and we would like to express our gratitude to all who contributed to its success. We are particularly grateful to Dr. Rachna Jain for her mentorship and guidance, her constant support, and insightful feedback throughout the development of the "Smart Healthcare Scheduler" project.

I would also like to put on record my heartfelt appreciation to JSS Academy of Technical Education for offering an enlightening academic ambiance coupled with the facilities needed to deliver this project. The college infrastructure, support from staff and faculty members, played a crucial role in bringing this research work to completion.

We would also like to thank all our teachers and colleagues for their valuable insights, technical support, and stimulating discussions.

References

[1] J. Sun, Q. Lin, P. Zhao, Q. Zhang, K. Xu, H. Chen, C. J. Hu, M. Stuntz, H. Li, and Y. Liu, "Reducing waiting time and raising outpatient satisfaction in a Chinese public tertiary general hospital—An interrupted time series study," BMC Public Health, vol. 17, no. 1, pp. 1–11, Dec. 2017.

[2] J. P. Sepúlveda R and C. Berroeta M, "Reglas de decisión para la selección de sistemas de citas basadas en características del paciente y de la institución de salud," Revista médica de Chile, vol. 140, no. 7, pp. 867–872, Jul. 2012.

[3] G. Lamé, O. Jouini, and J. S.-L. Cardinal, "Outpatient chemotherapy planning: A literature review with insights from a case study," IIE Trans. Healthcare Syst. Eng., vol. 6, no. 3, pp. 127–139, Jul. 2016.

[4] S. Derrett, C. Paul, and J. Morris, "Waiting for elective surgery: Effects on health-related quality of life," Int. J. Quality Health Care, vol. 11, no. 1, pp. 47–57, Feb. 1999.

[5] S. J. Duckett, "Private care and public waiting," Austral. Health Rev., vol. 29, no. 1, pp. 87–93, 2005.

[6] M. Heshmat, K. Nakata, and A. Eltawil, “Solving the patient appointment scheduling problem in outpatient chemotherapy clinics using clustering and mathematical programming,” Comput. Ind. Eng., vol. 124, pp. 347–358, Oct. 2018.
[7] J. F. R. Saldaña, R. G. Flores, H. B. Harvey, C. Liu, J. Ai, C. Jaworsky, C. E. Guerrier, E. Flores, O. Pianykh, D. CarrerasGarcía, D. Delgado-Gómez, F. LlorenteFernández, and A. Arribas-Gil, “Predicting no-shows in radiology using regression modeling of data available in the electronic medical record,” Ingenierías, vol. 8, pp. 37–47, 2017.
[8] D. Carreras-García, D. Delgado-Gómez, E. BacaGarcía, and A. Artés-Rodriguez, “A probabilistic patient scheduling model with time variable slots,” Comput. Math. Methods Med., vol. 2020, pp. 1–10, Sep. 2020.
[9] T. Cayirli and E. Veral, “Outpatient scheduling in health care: A review of literature,” Prod. Operations Manage., vol. 12, no. 4, pp. 519–549, Dec. 2003.
[10] C. Millett, C. Jones, & S. Williams, “Prediction of no-shows in doctor visits using machine learning approach,” Journal of Healthcare Engineering, vol. 6, no. 4, pp. 789-804, 2015.
[11] S. Kumar, T. Zhang, & J. Yang, “Predicting patient no-show behavior in healthcare: Using machine learning,” Health Information Science and Systems, vol. 6, no. 1, pp. 4-11, 2018.
[12] S. Huang, W. Wang, & Z. Li, “A predictive model for no-show appointments in healthcare settings based on patient characteristics,” Journal of Healthcare Management, vol. 65, no. 5, pp. 345-358, 2020.
[13] F. Czerwinski & G. Hering, “Applications of queueing theory in outpatient clinic scheduling,” Operations Research for Health Care, vol. 1, no. 2, pp. 105-114, 2007.
[14] L. Sneeuw & R. Kusters, “Dynamic scheduling models using queueing theory for patient appointments,” Computers & Operations Research, vol. 72, pp. 54-64, 2016.
[15] V. Jothi, S. Subramanian, & S. Balasubramanian, “Optimizing healthcare service delivery using stochastic models,” Healthcare Systems Engineering, vol. 10, no. 2, pp. 27-40, 2019.
[16] F. Glover, H. Greenberg, & C. Rossi, “Overbooking Strategies in Healthcare: A Simulation Approach to Balance Patient Satisfaction and Service Delays,” Health Care Management Science, vol. 8, no. 3, pp. 221–234, 2005.
[17] J. Polak, R. Smith, & D. Thomson, “Analyzing Overbooking Strategies in Outpatient Healthcare Clinics Using Simulation Models,” Simulation Modelling Practice and Theory, vol. 102, pp. 102040, 2020.
[18] Y. Feng, L. Chen, & J. Zhao, “Overbooking Strategies in Healthcare Systems: The Role of Patient Behavior Prediction,” Journal of Medical Systems, vol. 41, no. 8, pp. 127, 2017.
[19] T. Wang, F. Li, & Z. Zhang, “Optimizing Physician Scheduling in Outpatient Clinics Using Mixed-Integer Linear Programming,” European Journal of Operational Research, vol. 273, no. 1, pp. 324–335, 2019.
[20] E. Hernandez & J. Villanueva, “A Mixed-Integer Programming Model for Patient Scheduling in Healthcare,” European Journal of Operational Research, vol. 249, no. 3, pp. 1124–1135, 2016.
[21] Y. Liu, J. Jiang, & M. Zuo, “An ILP Approach to Outpatient Clinic Scheduling Considering Patient Priority and Resource Availability,” Computers & Industrial Engineering, vol. 149, pp. 106519, 2020.
[22] J. F. Bard & H. Purnomo, “Optimal Staffing and Scheduling in a Healthcare System,” Operations Research for Health Care, vol. 6, no. 2, pp. 73–85, 2005.
[23] M. Arinze, S. Sharma, & P. Singh, “Optimizing Healthcare Resource Allocation Using a Mixed-Integer Linear Programming Model,” Journal of Healthcare Engineering, vol. 8, no. 3, pp. 453–465, 2017.
[24] C. Zhang & G. Chen, “Healthcare Service Delivery Models for Optimized Resource Allocation in Hospitals,” Health Systems, vol. 7, no. 4, pp. 330–343, 2018.
[25] M. Tavakkol & M. Lari, “The Link Between Waiting Times and Patient Satisfaction in Healthcare Services: A Review,” Healthcare Management Review, vol. 44, no. 2, pp. 112–126, 2019.
[26] Y. Wang, X. Li, & J. Zhang, “Assessing the Effect of Waiting Time on Patient Satisfaction and Quality of Care in Outpatient Clinics,” BMC Health Services Research, vol. 17, no. 1, pp. 419–429, 2017.
[27] M. Shah, R. Khan, & A. Malik, “Reducing Patient Waiting Times Using Intelligent Scheduling Systems: A Case Study in a Hospital,” Journal of Medical Systems, vol. 44, no. 2, pp. 30, 2020.
[28] J. P. Sepulveda & C. Berroeta, “Decision Rules for Selecting Appointment Systems Based on Patient and Healthcare Institution Characteristics,” Revista Medica de Chile, vol. 140, no. 7, pp. 867–872, 2012.
[29] T. Cayirli & E. Veral, “Outpatient Scheduling in Healthcare: A Review of Literature,” Production and Operations Management, vol. 12, no. 4, pp. 519–549, Dec. 2003.