



# A comprehensive review on operating room scheduling and optimization

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## Abstract

The growing number of publications on Operating Room Scheduling (ORS) in recent years reflects the rapid advancements in the field. This review aims to comprehensively analyze the historical developments and evolving trends in operating room scheduling by systematically examining the literature from 2000 to 2023. A multi-database search, including Scopus, Web of Science, PubMed, ProQuest and IEEE Xplore was employed to ensure the inclusion of key studies. This paper presents a review of the factors, descriptive fields, and key issues in operating room scheduling. It also focuses on optimization techniques and solution approaches for both deterministic and uncertain conditions. Special attention is given to real-world constraints, such as resource limitations, staff availability and patient variability which significantly impact scheduling. The review identifies that ORS research covers a broad spectrum of problems and solutions, with no singular research trend dominating the field. This indicates that researchers are tackling diverse challenges across various contexts. The final section outlines the significant pitfalls and proposes future research directions, including the integration of emerging technologies and sustainability considerations. This review is a valuable resource for researchers, practitioners, and academicians in healthcare operations and hospital management, offering insights into current practices and future opportunities for innovation in ORS.

**Keywords** Operating room scheduling · Optimization methods · Healthcare management · Emerging technologies

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Extended author information available on the last page of the article

## 1 Introduction

A significant amount of research on operating room scheduling problems has been carried out, focusing on the different parameters. Previous research highlighted ORS problems from different points of view like importance of ORS in healthcare management, how important to optimize the ORS methods, modeling and solution techniques and application areas ORS related research. The development of algorithms, techniques and decision support systems to enhance resource utilization, patient priority, surgeon scheduling and emergency readiness have been the main topics of earlier research on operating room scheduling and optimization. Effective scheduling techniques can result in improved healthcare delivery, higher patient satisfaction, and more efficient use of scarce resources [1–4].

Operating rooms have been identified as a crucial financial aspect of hospitals. Based on approximations, the income generated by operating rooms constitutes over 40% of a hospital's revenue and accounts for nearly 30% of all hospital expenditures. As a result, the operating room is regarded as one of hospitals' most expensive functional departments as well as their primary profit center [5, 6]. The authors categorize the literature into six groups based on the scheduling timeframe or planning horizon. These categories include capacity planning, surgical services portfolio, process redesign and reengineering, schedule construction, schedule execution, and monitoring and control. While the precise costs associated with ORS for different-sized hospitals are unknown, some estimates indicate that OR costs in the US range from \$30 to \$90 billion yearly, or between 10 and 30% of all hospital costs [4, 7].

In 2019, Zhu used various techniques to get a thorough overview and a summary of the areas requiring attention. The papers show the regular utilization of heuristics and mathematical programming to address difficult problems related to linear and combinatorial optimization. Various methods are employed to evaluate the papers and obtain a comprehensive understanding of this field, while identifying specific areas requiring particular attention. The papers illustrate the consistent application of heuristics and mathematical programming to solve complex linear and combinatorial optimization problems [3]. According to [8], surgical procedures account for more than 60% of hospital admissions, which motivates hospital administrators to focus heavily on OR administration to enhance the scheduling and planning of surgical resources. The planning and scheduling procedures employed in practice significantly impact how well operating rooms perform.

Planning and scheduling operating rooms are known to be a difficult task because it necessitates the integration and interaction of numerous agents (e.g., patients, surgeons, nurses, and technicians) in an uncertain environment with capacity restrictions (such as the availability of expensive technological equipment) [5, 9, 10]. The literature review considers a range of factors, including decision levels, scheduling approaches, patient classifications, problem aspects as well as mathematical models, solutions, and methodologies. These aspects are carefully considered and evaluated in our analysis. The research analyzed in this study shows unequivocally that the performance of the surgical center is significantly impacted by decisions made at various levels [3].

ORS is one of the most frequently used applications in operation research. Since surgical procedures account for around 40% of the overall hospital cost, this topic has garnered the attention of prominent scholars [11]. A reliable estimation of case duration is required to construct an efficient OR schedule. Nevertheless, unforeseen occurrences such as canceled or urgent surgeries and unavoidable surgical complications can significantly impact the length of surgical cases. A wide range of circumstances other than these incidents influence the duration of the case. These elements can be divided into three main categories for the sake of simplicity: clinical, organizational, and logistical. The patient's health status is one of the most important clinical variables [12]. Effective OR schedules are judged on their capacity to carry out elective procedures as scheduled while also being adaptable enough to take into account unforeseen demands [6]. The effectiveness of the ORS schedules is assessed using a number of competing criteria. Common performance measures include patient throughput, OR utilization, patient and OR team waiting times, surgeon idle time, surgical cancellation rates, patient deferral rates, and staff, patient, and surgeon satisfaction scores. This study focuses on the performance measures that let us determine how well OR schedules can withstand unforeseen demands while including surgery duration as a stochastic element [1].

The motivation for this comprehensive review of operating room scheduling arises from the increasing demand for improved surgical efficiency and patient care within healthcare systems. As the complexity of scheduling grows due to factors such as patient variability and limited resources, it is essential to explore and synthesize existing research to identify best practices and innovative solutions [13]. Despite the substantial body of literature on ORS, significant research gaps remain, particularly in integrating the various factors influencing scheduling with advanced optimization techniques. Many studies often focus on deterministic scenarios, neglecting the critical uncertainties inherent in real-world surgical environments. Furthermore, there is a lack of comprehensive frameworks that evaluate the practical implementation of optimization methods in diverse healthcare contexts.

This research aims to address several critical questions to accomplish the goals of this study, ensuring alignment with the key findings from the review. The research questions focus on identifying the challenges, methodologies, and potential future directions for ORS:

**RQ1** What are the most significant factors and issues that affect the operating room scheduling?

**RQ2** What methods and techniques are most effective for managing operating room scheduling under conditions of certainty and uncertainty?

**RQ3** What solution approaches and validation techniques are used for optimizing operating room scheduling models?

**RQ4** What are the emerging technologies and sustainability-focused strategies that can be integrated into ORS to address current challenges and optimize future scheduling models?

The novel contribution of this research lies in the integration of both operations management and operations research perspectives within the field of ORS and optimization. By combining these two aspects, this study offers a comprehensive overview of the key factors, challenges, pitfalls, and optimization techniques in a single article. It addresses the practical constraints in OR scheduling while also presenting advanced solutions to overcome these limitations. Although ORS has been a growing focus in healthcare management science, particularly in recent years, there remains significant room for improvement, especially in managing scheduling and optimization under uncertainty. This study highlights these gaps and provides insights into emerging solutions, including adaptive models, AI integration, and real-time analytics, to enhance the practical applicability of ORS in real-world settings.

The remainder of the study is structured as follows: Sect. 2 outlines the research methodology. Section 3 presents the factors, issues, and descriptive fields related to ORS. Section 4 focuses on the practical challenges and methods to avoid common pitfalls. The study's limitations and future research directions are discussed in Sect. 5, while Sect. 6 concludes with the key findings and implications.

## 2 Methodology

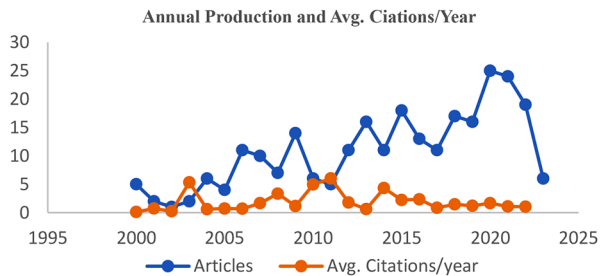
### 2.1 Study design

This research utilized a comprehensive search strategy to gather articles related to operating room scheduling (ORS). The initial literature search was conducted using the **Scopus** database, one of the largest multidisciplinary databases, providing extensive coverage of operations research and management science. However, to ensure a broader and more inclusive review, we expanded the database search to include **Web of Science**, **PubMed**, **ProQuest** and **IEEE Xplore**, as these databases are also highly relevant for capturing studies related to healthcare optimization, engineering, and management. The search query was designed to capture various terms related to OR scheduling and optimization: **Optimi?\* OR plan\* OR manag\* OR operat\* OR schedul\* AND operat\* room OR operat\* theatre**. The asterisk (\*) was used to include any variation of the search terms. For example, "operat" finds operate, operating, operation, etc. The search targeted the article's **title**, **abstract**, and **keywords**. The study emphasized articles in the categories of operations research, management science, healthcare, and engineering, focusing specifically on OR scheduling optimization. The search process followed a step-by-step approach, filtering results based on time span, language, document type, and subject area. Table 1 shows the detailed search criteria, databases, and filtering process.

The search period was set from **2000 to 2023** to capture the developments, trends, and future directions in OR scheduling and optimization over the last two decades. While Scopus was initially chosen due to its comprehensive coverage of operations management and optimization literature, the inclusion of other databases such as Web of Science, PubMed, ProQuest and IEEE Xplore broadens the scope and ensures that important papers are not overlooked. 260 documents were selected after applying all filtering criteria and removing duplicates. These documents were analyzed based

**Table 1** Search criteria and queries

Initial documents	This study got 18,150 documents using search terms.	
Topics	Databases	The authors mainly used Scopus as a database to extract literature. However, this research expanded the database search to include Web of Science, PubMed, ProQuest and IEEE Xplore.
	Search terms in the Research article	Title, abstract, author keywords and keywords plus
Filtered by	Time span	Limiting the time span to 2000–2023 reduced the documents to 8,610.
	Language	Restricting the search to documents written in English further reduced the number to 3,670.
	Document type	Limiting the search to articles, review papers, conference papers, book chapters, short surveys, and books yielded 1,276 documents.
	Subject area	Filtering by subject area limited to (Engineering, Computer Science and Engineering, Mathematics, Decision Sciences, Business, Management and Accounting, Health Profession, Nursing and Multidisciplinary), we got 265 documents
	Eye filtering	After manual screening for relevance and removing duplicates, the final dataset comprised 260 documents.

**Fig. 1** Analysis of ORS publications

on their contributions to ORS in terms of uncertainty, objective functions, specific scheduling needs, and different stages of the OR process. Additionally, this study conducted forward and backward reference searches to include relevant literature that may have been missed in the initial search process, further ensuring the comprehensiveness of the review. This multi-database search strategy helps to overcome the limitations of relying solely on Scopus and provides a more inclusive view of the current state of ORS research. By using these criteria, we aimed to ensure the selected articles' relevance and quality while focusing on the key areas of interest.

## 2.2 Data collection and analysis

Figure 1 presents an analysis of Operating Room Scheduling publications based on data from 2000 to 2023. It illustrates both the annual number of published articles and the average number of citations per year for the 260 articles included in this review. The data reveal a notable rise in the number of ORS publications since 2013, marking a significant acceleration in research interest and output. Prior to this surge, the annual publication rate remained relatively stable from 2008 to 2012, with a marked decline observed in 2010. This period of steady output was followed by a

sharp increase in publications, peaking in the years following 2013. However, while the volume of published research has grown, the average number of citations per article has decreased over time. This observation points to a shift in research focus within the field of ORS. During data analysis, it became evident that the last 15 years (2008–2023) have seen a major shift toward optimization-focused studies. As ORS research evolved, publications increasingly emphasized themes such as operating room scheduling and optimization [14–29], multi-objective optimization [30–43], and optimization under uncertainty [44–47]. In addition, research on machine learning [48–51], heuristics, simulation [20, 52–56], and multi-criteria decision-making methods [57–59] has gained prominence.

Despite the growing importance of outpatient surgery, research in this area has not experienced a corresponding increase. Most research continues to focus on block scheduling strategies and elective patients, with a limited number of studies considering holistic approaches or stochastic elements in OR operations. The growing importance of ORS in healthcare management has created significant demand for operational research and management solutions. Researchers have broadly categorized this field and outlined various methods and models, such as machine learning, predictive analytics, and prescriptive analytics, and their applications [60–66]. These advancements are shaping the future of ORS by offering innovative solutions for complex scheduling and optimization challenges.

### 3 Result and discussion

This research result and discussion are divided into two major categories (i) Review related to Factors, descriptive fields and Issues of ORS in research and (ii) Review related to optimization. A detailed description is given below.

#### 3.1 Different factors and issues in ORS research

##### 3.1.1 Patient characteristics

**3.1.1.1 Elective vs. non-elective** In the literature, patients are typically categorized into two groups: elective and non-elective. Elective patients have surgeries that can be planned in advance, while non-elective patients require urgent or immediate surgeries. Non-elective procedures are classified as emergencies when they need to be performed immediately and urgent when they can be delayed for a short time, though terminology may vary across studies [1, 3]. Most research focuses on elective patients. Interestingly, the expected increase in publications related to outpatient surgeries in non-hospital settings has not materialized. Some studies cover both elective and non-elective patients, resulting in a combined total that may exceed 100% [1].

**3.1.1.2 Inpatients vs. outpatients** Inpatient surgeries are those carried out on people who have been admitted to a hospital and are expected to stay the night for their care and recovery. Outpatient surgery, performed outside of a hospital setting, has distinct

characteristics compared to inpatient surgery. Outpatient procedures often involve standardized treatments, such as routine surgeries and minimally invasive procedures. The timing of outpatient arrivals for surgeries is uncertain, as these patients are not already in a hospital ward. These and other factors significantly influence the choice of scheduling techniques for outpatient surgeries [67–70]. There is a noticeable trend of services transitioning from inpatient to outpatient care, as indicated by the faster growth rate of the latter [71, 72].

### 3.1.2 Planning horizon in OR scheduling

The challenges associated with the surgical scheduling process can be categorized based on the planning horizon they address. This process entails various decisions that hospital administrators, surgeons, and their representatives must make. These decisions range from long-term planning, which involves creating or enhancing facilities, to medium-term allocations of surgical time blocks to surgeons. In the short term, decisions include assigning patients to specific days and times within those blocks, making last-minute adjustments, and executing the schedule accordingly [4]. A short-term surgical schedule, developed a few days to a few weeks prior to the procedure, includes a list of surgeries with uncertain durations and the corresponding operating rooms to which they are assigned. This schedule must adhere to certain requirements, including the surgeon's availability, any room preferences, and the type of OR in which the procedure can be carried out. Short-term OR planning aims to create a predictable workload with enough time for emergencies [4, 48].

### 3.1.3 Decision levels

The literature typically categorizes planning and scheduling decisions for operating rooms into three distinct levels: strategic decisions for the long term, tactical decisions for the medium term, and operational decisions for the short term. A detailed explanation and examples of these decision levels are presented in Table 2.

**Table 2** Decision levels in ORS

Decision levels	Definition/description	Examples	Reference
Strategic	The challenges primarily involve forecasting medium and long-term demand and allocating operating room time to specific medical specialties or surgeons. This decision-making process takes place over an extended timeframe and operates at a higher hierarchical level.	The challenges include capacity planning, capacity allocation and case mix-related issues.	[9] [73] [74]
Tactical	The issue pertains to the scheduling of operating rooms in a cyclic manner.	The master surgical scheduling problem	
Operational	The issue at hand is commonly referred to as the surgery scheduling problem, which entails selecting the specific date, time, and resources allocated for a particular surgical procedure.	The tasks include advanced scheduling, allocation scheduling and the integration of these two processes.	

### 3.1.4 Scheduling strategies

The three primary approaches used to study scheduling problems are block scheduling, open scheduling, and modified block scheduling strategies. Compared to the modified block scheduling strategy, the literature on block scheduling and open scheduling is significantly more extensive, as illustrated in Table 3.

### 3.1.5 Machine learning in ORS

The scheduling issue for operating rooms has received much attention in the literature. The issue lies at the nexus of operations research, machine learning, and health-care management. Machine learning and discrete optimization have considerably increased study and application. These two analytical fields have typically served two distinct functions within a single business decision-making dilemma. While operations research is utilized to build models and approaches to addressing scheduling problems, machine learning is mostly used to generate reliable predictions of surgical duration. Typically, machine learning techniques are employed to forecast what is likely to occur in the future, and optimization techniques are used to carefully consider all feasible solutions [84, 85].

Caserta et al., (2022) introduced a novel method for estimating the duration of surgical interventions at a medium-sized general hospital in Spain. They compared two methodological approaches machine learning and conditional density estimation methods to obtain reliable estimates of surgery durations [48]. Accurate time estimation is essential for applying management science scheduling methods to case scheduling. However, in many instances, the specific procedures to be performed on a patient are not known in advance, and even when they are, the exact durations remain uncertain. This complexity presents challenges for surgical scheduling. Nevertheless, having precise time estimates would facilitate case scheduling with fixed start times rather than the ambiguous “to follow” approach, enabling the implemen-

**Table 3** Different scheduling strategies

Strategies	Definition	Advantages	Reference
Block Scheduling	A block strategy divides the OR schedule into blocks that are given to different specializations. Regularly, surgeons are given time in a certain OR, and the associated resources are reserved in advance.	i) Scheduling is less complicated since surgeries can only be scheduled in blocks for the specific medical profession. ii) The goal is to minimize patients' total predicted weighted waiting time.	[4, 5, 46, 70, 75–79]
Open Scheduling	Appointments can be scheduled in any operating room (OR), providing greater flexibility in the scheduling process for all cases.	i) Surgeons are not prioritized in pre-booking specific block times in advance and can choose to perform surgeries on any workday in any available OR. ii) More flexible than the former	[70, 77, 80–83]
Modified Block Scheduling	Block and open scheduling techniques are combined in a modified block scheduling strategy that is flexible and workable for management needs.	Implementing certain policy changes allows for the utilization of block scheduling to be assessed and any instances of underutilization to be addressed.	[70, 77, 80–83]

tation of optimization and optimum-seeking scheduling techniques. These methods aim to maximize operating room utilization, enhance productivity, and reduce labor costs [4]. Surgery duration typically follows a probability distribution, and historical data suggests that the normal distribution is the best fit for the data [86].

Additionally, a density-based technique shows its benefits and shortcomings compared to the machine learning-based approach to develop a full distribution function rather than a point estimator to represent the length of a particular surgery. The authors in this research discuss some implications for using these prediction techniques to build a data-driven uncertainty set for the robust operating room scheduling problem [48]. Without using patient-related data, other authors calculate the surgical length for a situation that includes emergency and planned surgeries (i.e., electronic medical records). They incorporate a few organizational characteristics that are often known before scheduling to get around these restrictions. They emphasize their familiarity with the team, exposure to the surgeon, and conflict vs. cooperative patterns in the operating room [87].

For this purpose, the researchers separated the regular and predicted variables in the model into two sets. Operational constraints and objective function terms are modeled using regular variables, which are common in MIP. Predictive models are used to specify the predicted variables, some of which depend on conventional variables. The user uploads one of the three allowed predictive model formats, along with a mapping between the standard variables and the features, and then pre-trains the predictive models. This research employs linearization methods to incorporate these predictive models into an optimization model. This is simple for linear regression. They also used a piece-wise linear approximation for logistic regression [84]. Subsequently, nowadays, predictive modeling and optimization are combined in several study areas. First of all, optimization strategies empower machine learning algorithms. For instance, the ordinary least squares method can be used to estimate the unknown parameters in a simple linear regression model by minimizing the sum of the squares of the differences between the observed values of the dependent variable and the fitted values. Different optimization approaches are used in machine learning to make the learning process effective and attain the desired accuracy [50].

### 3.1.6 Uncertainty in ORS

The uncertainty around surgical services is one of the main issues with developing precise OR planning and scheduling techniques. While stochastic approaches openly include uncertainty, deterministic planning and scheduling approaches ignore it. The literature discusses various types of uncertainty including duration, arrival, resource and care requirement uncertainty. Surgery processing time is referred to as surgery duration [14, 30, 68–70, 88–90]. The main cause of the overall complexity of OR planning is uncertainty. If previous procedures end early, patients in the OR may not always be available to start surgery earlier than scheduled. The period between pre-surgery, surgery, and patient recovery varies greatly. Operating room planning remains challenging, even when managers clearly understand the probability distribution of surgery durations [91].

Duration uncertainty is a significant aspect of operating room scheduling (ORS) uncertainty. Denton et al. (2010) focused on making decisions related to the number of operating rooms to be opened and the allocation of surgery blocks in ORS. On the other hand, Batun et al. (2011) took into account not only the allocation of surgery blocks but also the sequencing of patients and the start times of surgeons. Both models seek to reduce the costs associated with OR opening and overtime and also take into account surgeon idle hours [90, 92]. The uncertainty of surgery duration is one of the most significant factors in the complexity of patients' planning and scheduling issues because it is influenced by numerous factors, even in similar surgeries, due to specific patient conditions, since the duration of surgery and the requirement for using special tools are different. Additionally, the presence of a surgeon's assistant during any surgery might improve the results of the procedure by shortening the procedure's duration and lowering the likelihood of mistakes.

Duration uncertainty is a crucial aspect of ORS uncertainty. For instance, one study focused on decision-making regarding the number of operating rooms to be opened and the allocation of surgery blocks in ORS. In contrast, another study considered not only the allocation of surgery blocks but also the sequencing of patients and the start times for surgeons. Both models aim to minimize costs associated with OR opening and overtime while also addressing surgeon idle time [90, 92]. The uncertainty of surgery duration is a significant factor contributing to the complexity of planning and scheduling patients, as it is influenced by various factors, even among similar procedures, due to individual patient conditions. This variability arises from differences in surgical duration and the need for specialized tools. Furthermore, having a surgeon's assistant present during surgery may enhance outcomes by reducing the procedure's duration and minimizing the risk of errors.

Predicting the length of surgery is challenging since, in some cases, the scope of the procedure is only obvious once the treatment is underway. Additionally, the lengths of time frequently depend on various intricate aspects, such as the patient's traits, the physician's, and the surgical team's. The total workload per OR needs to be clarified due to the uncertainty of individual surgery durations. In 44% of all publications, duration uncertainty is taken into account, whereas in 28%, arrival uncertainty is considered [1]. The researchers can adopt two methodological approaches, (i) Machine Learning and (ii) Conditional Density Estimation methods, to estimate the surgery duration more accurately [48]. Robust optimization serves as a technique for optimization under uncertainty. Generally, robust optimization enhances the framework by optimizing across an uncertainty set rather than relying on a single-point estimate of the uncertain parameter. However, it is widely acknowledged that traditional robust optimization strategies, which focus on protecting against worst-case scenarios, often yield excessively conservative results. With this in mind, the authors aim to explore various approaches both predictive and prescriptive to mitigate these effects [3, 16, 93].

## 3.2 Optimization oriented review

### 3.2.1 Problem definition, assumptions and objective functions in ORS research

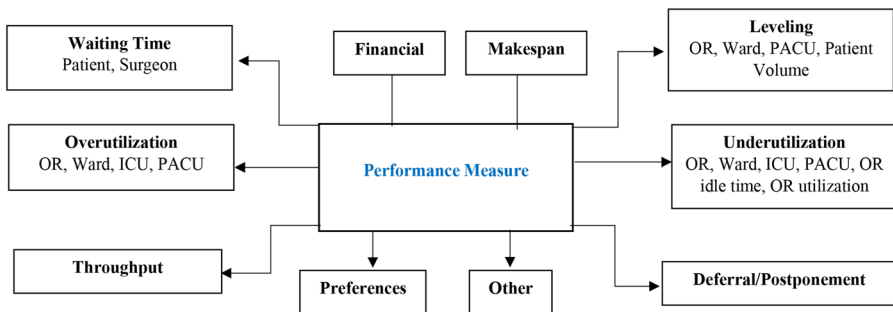
Numerous articles have identified a problem that is unique to a particular hospital, shedding light on whether a solution can be applied to different contexts and to what extent. Van Essen et al. [94] surveyed a number of institutions to support the generality of their modeling assumptions. When generalizable approaches are introduced, spreading and applying effective operations research techniques across multiple hospitals is simpler.

In ORS research, problem definition typically revolves around optimizing the allocation of resources, such as operating rooms, medical staff, and patient scheduling, while minimizing inefficiencies like idle time, overtime, and patient waiting times. To fully grasp the problem statement, it is essential to establish specific assumptions, which generally relate to information about the patient, the facility, and the underlying issue. Assumptions in ORS models often include fixed surgery durations, known patient arrivals, and resource availability, though some models account for uncertainties like emergency cases and variable surgery lengths [92, 95]. When employing mathematical programming (MP) or an improvement heuristics to tackle the problem of patient-to-date assignment, it is typically assumed that the patient population requiring scheduling is predetermined in advance. This assumption is frequently stated and is clear from the problem definition. This review found that it was occasionally challenging to categorize some articles since the necessary information was either absent or hard to locate. As a result, assumptions must be made more explicit. Also, the assumptions must be more straightforward and more accurate for academics and professionals to decide whether an item is relevant to them. The assumptions include the distribution of surgical durations and the length of stay in downstream units for patients. With regard to the hospital, the assumptions primarily focus on policy and capacity planning. We found that papers using analytical methods, MP, and improvement heuristics are generally harder to identify than those using method-based assumptions. Some changes must be made to the current literature to clearly define ORS problems and use reasonable assumptions [1].

The objective functions in ORS research aim to balance multiple criteria, such as maximizing resource utilization, minimizing costs, reducing patient waiting times, and improving overall surgical efficiency. These objectives are often framed within mathematical programming models, such as mixed-integer programming, or through heuristic and simulation-based approaches [75–77, 95]. Under/overtime or under/overutilization are frequently included in the optimization model's objective function. While two-thirds of MP models contain multiple objectives, those performance measures are rarely used on their own but are typically a component of a multi-objective formulation [1]. Basically, all of the goals are geared toward maximizing the operating room's effectiveness and lowering resource costs. Researchers frequently look for solutions to the problem of determining the sequence of relevant patients by minimizing the total costs associated with projected waiting times and estimated idling costs for resources, such as operating rooms and medical teams [95]. Table 4 summarizes the primary objective functions of the reviewed studies.

**Table 4** Goals and objectives of ORS in the literature

Goals	Functions	References
Maximize	The number of surgical cases to be scheduled	[70, 75–77, 92, 95–97]
	The use of ORS time	
	The satisfaction	
Minimize	The cost of operating rooms	[70, 75–77, 92, 95–98]
	Patient-related costs	
	The costs of patients' waiting time	
	The number of operating rooms and required beds	
	The maximum makespan	
	The overtime	
	The number of used blocks	
	The transitions of surgeons between different ORs	

**Fig. 2** Various performance measure

### 3.2.2 Performance measures

To accommodate the diverse interests of stakeholders in operating room scheduling (ORS), researchers often integrate multiple performance metrics. A common approach is the use of a weighted sum of these measures, allowing for a balanced assessment of various factors. The key performance indicators (KPIs) used in ORS research include waiting time, resource utilization, workload balancing, idle time, throughput, patient preferences, financial outcomes, makespan and patient deferral rates. These metrics provide a comprehensive view of both operational efficiency and patient-centered outcomes. Figure 2 and the following insights are derived from an extensive review of the literature [1, 5, 7, 9, 30, 39, 40, 67–70, 74, 80, 88–90, 92, 99–101].

- Patient waiting time is a frequently used performance metric, encompassing both direct waiting time (delays on the day of surgery) and indirect waiting time, or access time, which is linked to the size of the waiting list. The type of waiting time evaluated may differ depending on the focus of the study and the decision being analyzed.
- The most often used performance metric is still overtime. Preference-related met-

rics gained popularity starting in 2008; however, after 2010, there was a fall in interest.

- Patient throughput is used somewhat infrequently. It is a numerical measurement that is frequently linked to the number of patients served.
- Utilization relates to a resource constraint, whereas undertime or overtime also involves timing. As a result, it is conceivable to have an OR that is underutilized but still runs overtime. Which point of view is being used varies among articles. As a result, some of the research combines underutilization with undertime and overutilization with overtime.

Minimizing overtime is a key objective in operating room scheduling research, as working additional hours can lead to staff dissatisfaction, increased hospital costs (due to higher wages for overtime), surgery cancellations, and disruptions in downstream departments. Dexter and Macario [102] found that consistently underestimating case durations did not significantly impact OR overutilization, as the likelihood of procedures exceeding expected durations remained low. Another researcher proposed an analytical approach that considers both stochastic surgical schedules and the unpredictable arrival of emergency patients, demonstrating how the probability of schedule overruns varies with the number of surgeries scheduled each day [103]. To minimize deviations from specified utilization levels for the operating room (OR), intensive care unit (ICU), medium care unit, and nursing staff, the researchers formulated an optimization problem that quantified the total of overutilization and underutilization to assess the deviation [67].

Preference-related metrics often include a qualitative component and have garnered considerable attention in both healthcare and operations research literature. Approaches focused on value and quality are becoming increasingly significant. For instance, a study on cataract surgery patients found that their preferences included receiving care on their chosen day, at a single location, in one visit, and preferably in the morning [102]. Patient priorities also reflect preferences, as demonstrated in models presented by [104, 105], where patients' positions on waiting lists were determined by priority scoring algorithms considering the urgency of their condition, pain, dysfunction, disability, and waiting time. Priority scoring effectively reduces the weighted waiting time for all patients, while equal patient priorities in an algorithm result in decreased average patient waiting time.

### 3.2.3 Decision delineation and facilities

In the literature, researchers often use a matrix to detail the decisions being evaluated, such as selecting specific days, times, spaces, or capacities for scheduling. Articles are typically categorized based on the decision levels they address or the target audience for those decisions. For instance, distinctions are made between decisions at the specialty, surgeon, or patient level [14]. Operating room planning and scheduling are influenced by numerous factors, including bed capacity issues [106], operating room to ward assignments [107], patient-to-week allocations, and scheduling aspects like recovery time in the OR [70]. Since OR scheduling impacts multiple departments, an integrated approach that considers both upstream (e.g., outpatient clinics) and down-

stream (e.g., ICU, PACU) facilities is essential for optimizing resource utilization and improving overall hospital efficiency. This integrated approach aims to enhance the overall performance of these interconnected facilities. Ignoring this integration could undermine the effectiveness of the associated facilities [1, 67, 69, 70].

Throughout the years, the percentage of articles that address the OR in an integrated manner has remained a more significant portion of the research. This is unexpected, given that models are becoming more complicated and that there should be a growing interest in integrated methodologies. Approximately half of the previous research articles incorporated an integrated approach to planning and scheduling in the operating room. The most commonly included downstream facilities in these integrated methods were the PACU, ward and ICU. It's important to note that only these three primary downstream facilities were explicitly mentioned, so their count may not always align with the total number of integrated approaches discussed in the articles [1].

### 3.2.4 Operations research methodology in ORS

The literature on OR planning and scheduling highlights a variety of operations research methodologies. These approaches are used to evaluate and analyze the impact of specific changes in the problem environment. Techniques such as mathematical programming, simulation, heuristics, and stochastic models are commonly employed to optimize resource allocation, improve efficiency, and reduce costs in ORS. These methods enable researchers to explore different scenarios, manage uncertainties, and propose solutions for complex scheduling challenges in healthcare settings [67–70]. The research on OR scheduling demonstrates that surgical services are characterized by intrinsic durational uncertainty. Due to the very diverse character of surgical cases, it is evident that ambiguity is a significant problem [77]. The challenges of operating room scheduling become considerably more complex when accounting for factors like uncertainty, including variations in surgery durations and emergency interventions. While stochastic approaches seek to address this uncertainty and unpredictability, many OR planning and scheduling problems continue to assume deterministic surgery durations, thereby overlooking these critical factors. However, the inherent uncertainty in surgeries, including unexpected arrivals of emergency patients, affects the duration of individual surgeries and impacts the overall surgery schedule. The ability of operations research approaches to handle stochasticity should be obvious, and in particular, simulation techniques and analytical processes seem to be well suited. These issues can also be resolved using stochastic programming, such as two-stage linear programming. Only a small percentage of papers, though, employ this method to address actual issues [30, 67–70, 76, 88, 89, 108].

An optimization approach was introduced for rescheduling patients on the day of surgery, where elective and non-elective patients are reordered in each operating room after each procedure [109]. This method employed a branch-and-bound technique to maximize weighted throughput while simultaneously reducing patient cancellation rates. Similarly, another study focused on rescheduling elective patients in the presence of emergency arrivals, employing Mixed Integer Programming (MIP) and a genetic algorithm to minimize interruption costs while considering both the

OR and the PACU [110]. Additionally, a decision support system was developed to provide suggestions to the OR manager for addressing scheduling issues, using Mathematical Programming to derive decision rules, such as whether to reschedule a procedure or introduce gaps between surgeries [94]. Another study introduced a chance-constrained overtime model that employs the normal approximation of the sum of procedure durations within a day in the OR. This model offers nearly optimal solutions for assigning surgeries to time blocks, and through the use of actual data, it was shown to be particularly effective for specialties with high patient volumes per OR day [105]. The major findings from the previous literature are:

- Only mathematical programming experienced a significant increase in popularity among the main solution methods utilized in literature [1, 111].
- Since various situations, settings, or options are contrasted concerning the performance measures, authors refer to this method as scenario analysis. Scenario analysis is common and is frequently done in the literature on discrete-event simulation (DES) modeling [1, 111, 112].
- Constructive algorithms, improvement heuristics, and mathematical programming are widely employed. Unlike DES and analytical models, combinatorial optimization issues are the focus of MPs like mixed integer programming [1, 111, 112].
- A recent study introduced an MIP framework designed to minimize inactivity and patient wait times while optimizing the allocation of high-priority resources. The model incorporates both upstream and downstream units, including the Pre-operative Holding Unit (PHU), PACU and ICU [113].
- The papers are assessed using various methods to get a thorough overview of this area, and the fields that need special attention are outlined. It demonstrates how heuristics and mathematical programming are routinely used to solve challenging linear and combinatorial optimization issues [3].
- Some authors used linearization methods to include these predictive models in an optimization model. This is simple for linear regression. For instance, authors use a piece-wise linear approximation for logistic regression [84].
- Researchers proposed a binary programming model to optimize operating room scheduling for elective patients, to minimize idle times and maximize surgeries within optimal time windows. The study utilizes a Lagrangian relaxation method and sub-gradient techniques to simplify and improve the effectiveness of the NP-hard model in coordinating both operating and recovery rooms [114].

### 3.2.5 Solution methods/approaches in ORS research

Surgical planning and scheduling problems have led to the development of numerous practical solutions and methods. The size and complexity of the optimization problem in operating room planning and scheduling influences the choice between exact methods and meta-heuristics. These solutions can be classified into exact algorithms, mathematical programming, heuristics, simulations, and Markov decision processes.

An overview of the commonly employed methods for addressing these OR planning and scheduling challenges is provided in Table 5.

The solutions that are appropriate in the circumstances are shown in Table 6.

### 3.2.6 Testing phase, exploratory data analysis and application

Many researchers provide a comprehensive testing phase to demonstrate the applicability of their findings. A sizable amount of data is desired, whether applicability focuses on computational effectiveness or on illustrating the extent to which objectives may be accomplished. There are different types of data previously used in literature: Real, theoretical, simulated, and data applied in practice. From the literature, it is evident that most of these data are based on actual medical procedures. This development is notable and has been facilitated by improved hospital information systems, which enable the seamless retrieval of data [5, 30, 39, 67–70, 74, 76, 88–90].

Exploratory data analysis involves a number of surgeons, operating rooms, and surgical specialties or services. Each surgical record consists of different variables pertaining to the patient, anesthetic, surgical case details, and segmented operation hours. For exploratory data analysis, permission from an authorized body is required. The permission required to work with fully de-identified surgical data from a hospital granted by the Institutional Review Board (IRB) [121]. The hospital's records have been categorized and filtered using data mining approaches. Thus, each surgical record in the data set has been assessed during the data quality evaluation phase to plan the data cleansing and enrichment techniques. This procedure revealed problems with the data set's data quality. Specifically, missing values, inconsistent entries, duplicate data, and time components with unusual durations were filtered out from the surgical records (a deviation of  $\pm 3\sigma$  from the mean was considered a data entry

**Table 5** Solution approaches

Solution Approaches	Types	References
Exact Algorithms	<ul style="list-style-type: none"> <li>• Column generation</li> <li>• Branch and bound</li> <li>• Branch and cut</li> <li>• Branch-and-price</li> <li>• Dynamic programming</li> </ul>	[30, 34, 39, 40, 99, 100, 115, 116]
Mathematical Programming	<ul style="list-style-type: none"> <li>• Linear programming</li> <li>• Integer Programming</li> <li>• Mixed Integer Programming</li> <li>• Goal Programming</li> </ul>	[30, 67–70, 76, 88, 89]
Heuristics	<ul style="list-style-type: none"> <li>• Heuristics based on exact methods</li> <li>• Heuristics based on linear programming</li> <li>• Heuristics based on dispatching-rule</li> <li>• Metaheuristics</li> <li>• Constructive heuristics</li> <li>• Improvement heuristics</li> </ul>	[24, 30, 31, 34, 39, 40, 70, 75, 77, 82, 92, 117–119]
Simulation	<ul style="list-style-type: none"> <li>• Monte Carlo simulation</li> <li>• Discrete-event simulation</li> <li>• Others</li> </ul>	[38, 73, 80, 120]
Markov decision process	<ul style="list-style-type: none"> <li>• Continuous Markov decision process</li> <li>• Discrete Markov decision process</li> </ul>	[3, 23]

**Table 6** Solution approaches: questions and answers

Questions	Answers
Why exact algorithm?	In contrast to heuristics, which occasionally result in inferior solutions, an exact algorithm is the one that consistently finds the best solution to an optimization issue; approximation algorithms are a subset of these. Small-scale situations frequently employ exact algorithms [1], [3].
Why Mathematical Programming?	MP is used in planning and scheduling decision-making processes. The decision-making rules are derived using an MP, for instance, by scheduling a break between two surgeries or shifting a surgery. MIP is used to optimize the daily operational schedules. While two-thirds of MP models contain multiple objectives, those performance measures are rarely used on their own but are typically a component of a multi-objective formulation [1], [3].
Why Heuristics?	Heuristics are recommended when MP approaches become computationally challenging to solve within a reasonable time frame. To tackle the patient scheduling problem, one study employs a column generation-based algorithm [116].
Why simulation?	Simulation experiments are frequently conducted to assess the performance of proposed models in the context of OR planning and scheduling across various scenarios. Unlike queuing models, simulation models do not yield closed-form solutions but provide greater flexibility regarding the assumptions related to the probability distributions of surgical durations. Many studies employ simulation approaches, particularly when dealing with stochastic elements, to tackle the challenges associated with OR planning and scheduling [1], [3].
Why Markov decision Process (MDP)?	Markov Decision Processes (MDPs) provide a flexible framework for analyzing and solving a wide range of optimization problems, including those approached through dynamic programming (DP) and reinforcement learning. MDPs are applicable in various fields, such as robotics, automatic control, economics, and manufacturing. When it comes to managing the distribution of patients among servers and appointment times, MDPs are considered a practical and effective stochastic dynamic programming approach [3], [23].

error). To ensure accurate data for model development, surgical records in the dataset that did not meet the inclusion criteria were removed [122, 123].

Certain issues arise less frequently and can be illustrated using a case-mix model as an example. Each year, the implementation level may vary, making direct comparisons of articles on this subject challenging. Despite the potential for research implementation, authors frequently provide limited details about the implementation process. Consequently, we advocate for sharing more comprehensive data regarding the behavioral factors related to actual implementation. The research community would greatly benefit from identifying the factors that contribute to the success or failure of implementation efforts [30, 100, 124].

## 4 Practical challenges and common pitfalls

### 4.1 Practical challenges/constraints

In most cases, scheduling models assume complete flexibility in sequencing decisions, where surgeries can be easily rescheduled based on available time slots and resources. However, in real-world scenarios, various additional constraints and limitations significantly impact these decisions. For instance, scheduling complex surgeries early in the day is often beneficial because it ensures that key resources, such as

skilled personnel and specialized equipment, are readily available to address potential complications. Hospitals may also schedule day-of-surgery cases that require inpatient admission earlier in the day to increase the likelihood of securing an available hospital bed post-surgery. Additionally, certain cases may be scheduled at specific times of the day due to infection control protocols. For example, patients with infectious diseases may be scheduled later in the day to minimize the risk of contaminating operating rooms and other hospital areas. Staffing limitations also present significant challenges. Surgeons, nurses, and other healthcare professionals often have conflicting responsibilities, such as pre-and post-surgery consultations or outpatient clinics, which directly influence operating room sequencing decisions. The availability of these critical staff members throughout the day can limit the flexibility of the schedule. Furthermore, resource availability (e.g., diagnostic tools, specialized equipment) can restrict the number of concurrent operations that can be performed. For instance, surgeries requiring the same type of equipment or resources may need to be spaced apart due to limited availability, impacting scheduling efficiency. As a result, resource constraints like staff availability, equipment limitations, and post-surgical bed space need to be factored into scheduling decisions. Simply resequencing surgeries without considering these practical constraints could lead to infeasible schedules, increased waiting times, and potential disruptions in hospital operations [1, 80].

## 4.2 Common pitfalls and ways to avoid

Several common pitfalls can impede the progress of ORS research. To overcome these challenges, the authors emphasize the importance of following the guidelines outlined in Table 7, adapted from Samudra et al. [1]. By implementing these strategies, researchers can enhance the quality and applicability of their work, ultimately advancing the field of operating room scheduling.

## 5 Limitations and future directions

### 5.1 Limitations of this review

Some readers may have different search criteria than those mentioned in this review and may need to find articles accordingly. For example, they may be interested in articles based on the planning horizon's duration, the hospital setting's size, or the arrival pattern of patients (batch or individual). The review primarily relies on the Scopus database, although most relevant articles can also be found in databases such as Web of Science, PubMed, ProQuest and IEEE Xplore. However, the review does not specifically classify articles based on target groups (e.g., hospital size, location, or patient types), though such distinctions may sometimes be inferred from the results and discussion sections. Classifying articles by target groups is subjective and may vary based on the reader's specific needs, which is another limitation of this review. One critical limitation of this review is that it does not sufficiently address practical constraints in ORS implementation, such as staffing shortages, equipment limitations

**Table 7** Common pitfalls and ways to avoid

Pitfall Based on	Definition/ Description	Ways to Avoid
Clarifying the target group	It is necessary to distinguish between theoretical publications offering cutting-edge ideas and applied studies demonstrating how these methods can be used in practice. This distinction enables articles to concentrate more effectively on their core competencies. Furthermore, it facilitates easier access for scholars and practitioners seeking relevant publications.	Follow guidelines specific to the intended audience to effectively target practitioners or researchers. Differentiate your problem definitions, research tasks, conclusions, and findings properly. Determine the target market consistently and take into account adjusted publication incentives to encourage this differentiation.
Clarifying the objective	Many PMs, like overtime, are used in articles regardless of the issue being addressed. As a result, the most effective PMs for a particular context are not always the most frequently cited ones in the literature.	Two steps are recommended to select suitable performance measures. (i) Prioritise PMs that are valuable to hospital stakeholders. (ii) ensure the inclusion of model elements that are key drivers of the selected PMs. For example, accurately predicting surgical duration requires incorporating a realistic surgical duration model.
Clarifying the problem	Lack of information in papers makes it more difficult for readers, especially practitioners, to judge the applicability of research findings. Due to the assumption that all durations will be the same, caution should be required when applying analytical approaches like Markov models to inpatient scheduling.	It is critical in research to clearly describe and defend the context and method-specific assumptions. This is critical since readers may be unfamiliar with the procedures used, and having all assumptions stated allows them to assess the method's relevance and outcomes.

and variability in patient needs. These factors play a crucial role in the real-world application of ORS models and should be considered in future studies. For instance:

- **Staffing Issues:** OR schedules often face disruptions due to limited availability of surgeons, nurses, and other healthcare professionals, making theoretical models difficult to apply.
- **Equipment Limitations:** Operating rooms rely heavily on advanced equipment, and delays or breakdowns can significantly impact scheduling, which most models do not account for.
- **Patient Variability:** The variability in patient conditions, surgery duration, and emergency cases adds complexity to scheduling that is not adequately addressed in many studies.

## 5.2 Future directions

Future research in ORS should focus on addressing current limitations and exploring emerging opportunities. A future research recommendation involves comprehensively analyzing multi-objective ORS. Additionally, more attention should be given to the development of novel and hybrid solutions to address real-world OR scheduling challenges. These challenges include uncertainty in surgery duration, patient

needs variability and resource constraints. Priority should be given to research that focuses on integrating real-time decision support systems, AI-based solutions and sustainability considerations into ORS optimization. Bibliometric analysis could provide insights into emerging trends and help identify research gaps. The overall future directions are prioritized as follows:

### 5.2.1 High priority: integration of emerging technologies

- **Artificial Intelligence (AI):** AI-driven models can enhance ORS by predicting surgery durations, optimizing schedules, and adapting to real-time patient and staff availability changes. Researchers should explore how AI can be integrated with existing optimization techniques to improve decision-making in unpredictable environments.
- **Real-Time Data Analytics:** Incorporating real-time data on patient conditions, staff availability, and equipment status will allow for dynamic scheduling, reducing downtime and improving resource utilization. This is an area where significant progress can be made, particularly with advances in wearable technology and hospital information systems.
- **Robotic and Computer-Assisted Surgery:** Robotic and computer-assisted surgery uses advanced robotics and technology to enhance surgical precision and control. Surgeons use computer consoles to operate robotic equipment, which allows for more precise motions, smaller incisions, and more precision than traditional surgery. This strategy can result in speedier recovery times and fewer complications. It is especially effective in complex operations like urology, cardiology, and oncology, where precision is required.
- **Digital Twins:** Digital twin technology, which creates a virtual model of the hospital environment, can be used to simulate various OR scheduling scenarios, helping to test and refine scheduling strategies before implementing them in real-world settings.

### 5.2.2 Medium priority: sustainability in ORS

- **Green Operations:** Future research should focus on optimizing OR schedules for efficiency and sustainability. This includes minimizing energy use, reducing waste, and optimizing the use of disposable surgical supplies.
- **Sustainable Facility Design:** Future research should explore how operating room layouts, ventilation systems, and lighting can be optimized for energy efficiency and environmental sustainability. This includes investigating how architectural design and smart technologies can reduce energy consumption and resource use in ORs, contributing to greener healthcare practices.
- **Sustainable Resource Allocation:** Properly allocating human and material resources to minimize the carbon footprint while maintaining operational efficiency should be a key focus of future studies.

### 5.2.3 Medium priority: addressing practical constraints in ORS

Research should focus on creating adaptive ORS models that can respond to practical constraints such as staff shortages, equipment downtime, and emergency cases. This could involve developing hybrid models that combine simulation with optimization techniques, enabling real-time adjustments to schedules based on changing circumstances. Additional research topics include:

- **Patient Bulking Behavior:** Researchers should investigate patients' bulking behavior when multiple patients are scheduled together and how this affects OR utilization and patient wait times. Case studies can also be used to examine the impact of different modeling assumptions in OR scheduling.
- **Inpatient and Outpatient Schedule Integration:** Future research should focus on integrating inpatient and outpatient schedules to ensure a smooth flow of patients, prevent bottlenecks, and optimize resource utilization across departments.
- **Patient-Related Data Utilization:** Using patient-related data to estimate surgery lengths for emergency and planned surgeries is crucial for developing accurate ORS models. Incorporating such data can help improve scheduling accuracy and reduce surgery delays.

### 5.2.4 Low priority: optimization of multi-operating room schedules

Research should also explore methods to optimize schedules across multiple operating rooms. This includes planning an optimal surgical mix across different rooms, ensuring efficient weekly and monthly scheduling, and reserving operating room capacity for last-minute emergencies.

Future research should focus on developing solutions to these practical challenges, such as adaptive scheduling models that dynamically adjust to real-time resource availability and predictive tools for better management of patient variability. The integration of AI, real-time data analytics, and sustainability into ORS will be key drivers of innovation in the coming years, particularly in optimizing resource use and reducing environmental impacts while maintaining efficiency.

## 6 Conclusion

Operating room scheduling is a critical aspect of hospital management, with direct implications for resource utilization, patient care, and overall operational efficiency. This paper presents a comprehensive review of ORS research from 2000 to 2023. This study highlights various factors, challenges, and optimization techniques in ORS by examining key trends, gaps, and emerging strategies. The research categorizes decision levels into strategic, tactical, and operational and reviews scheduling strategies such as block, open, and modified block scheduling. This review offers actionable insights for healthcare management, helping decision-makers improve scheduling practices to optimize resource allocation, reduce waiting times, and enhance oper-

ating room utilization. The integration of both deterministic and stochastic models provides hospitals with tools to manage uncertainties in surgical durations and patient flow, leading to more efficient OR operations. In addressing the research questions, RQ1 (key factors and issues in OR scheduling) is supported by the exploration of decision levels and various scheduling strategies. RQ2 (methods for managing uncertainty) is backed by the review of stochastic models and uncertainty management techniques. RQ3 (solution approaches and validation methods) is reflected in the analysis of mathematical models and their real-world applications. RQ4 (Emerging technologies and sustainability considerations) proposes future directions by identifying technologies such as AI, machine learning, and real-time data analytics as key drivers for optimizing OR scheduling models. Additionally, sustainability-focused strategies are crucial for integrating environmental considerations into OR scheduling, promoting eco-friendly and cost-effective practices in healthcare.

## 6.1 Key findings and recommendations

This study highlighted several noteworthy findings and recommendations, as summarized below:

(i) Findings from the factors, issues and descriptive fields oriented-review perspectives, we found that:

- Throughout the past 15 years, the number of technical publications produced has dramatically increased.
- Surprisingly, despite their growing importance, research on outpatient surgery is not growing.
- The block scheduling strategy has been extensively studied compared to the other two scheduling techniques.
- Elective patients have received more focus in recent publications compared to non-elective patients.
- The number of studies that examine the OR holistically is not rising.
- Only 28% of papers take into account stochastic arrivals.

(ii) Based on the perspective of the optimization-oriented review, several findings were identified:

- Overtime and patient wait times are the most commonly used performance measures.
- Day and room assignment problems have been studied more extensively compared to capacity and timing-related issues.
- Surgeon availability and prioritizing higher-priority patients are the most common personnel and preference restrictions.
- Utilization and waiting time are the primary performance metrics explored, whereas patient postponement, preferences, and completion time have received comparatively less attention.
- Mathematical programming is the most popular approach, and it is mentioned in

approximately half of publications. Its usage has increased over the past 15 years.

- Uncertainty, mathematical modeling, and multi-objective functions are areas of strong interest among researchers, with uncertainty in surgery duration being a particularly prominent focus.
- Simulation-optimization and meta-heuristic strategies have been the primary focus of researchers in addressing OR problems in recent decades, each with its advantages and limitations.
- Capacity issues addressed at the discipline level often involve analytical and Discrete Event Simulation (DES) models, with DES models being validated using real data.
- Analytical approaches have fewer performance measures and constraints compared to DES models.
- Many researchers validate their developed approaches using real-world data, but there is still a noticeable lack of focus on implementation outcomes. Future research should investigate how these models can be practically implemented in diverse healthcare settings to ensure adoption and sustainability.

(iii) Based on the findings, this research recommends the following:

- Researchers should focus on developing and validating real-time OR scheduling models that incorporate uncertainty in surgery durations, as this remains a major challenge.
- There is a need for more research on outpatient surgeries, particularly as the transition from inpatient to outpatient care continues.
- Future studies should focus on the holistic integration of upstream and downstream departments (e.g., ICUs, wards) in OR scheduling models to improve resource coordination across hospitals.
- Given the complexity of OR environments, hybrid models that combine machine learning with simulation and optimization techniques could offer powerful new insights and solutions.
- Researchers should focus on emerging technologies and sustainable strategies to enhance operational efficiency, improve patient outcomes, and promote environmentally responsible practices in healthcare settings.
- Researchers should prioritize creating more user-friendly and adaptable OR scheduling software to bridge the gap between theoretical models and practical implementations in healthcare settings.

In conclusion, this review is relevant to surgical planning committees, OR managers, and directors. Future work should emphasize the integration of stochastic models that consider surgical time uncertainty to improve daily OR schedules. Additionally, researchers should explore the integration of new technologies such as artificial intelligence and digital twins to facilitate adaptive and real-time scheduling.

## 6.2 Academic and practical implications

This comprehensive review of OR planning and scheduling literature from 2000 to 2023 highlights several academic and practical implications.

### (i) Academic Implications.

From an academic perspective, this study contributes to a deeper understanding of the existing models, methodologies, and decision levels in OR scheduling. The analysis identifies gaps in the current literature, particularly in integrating uncertainty management and applying emerging technologies like AI, machine learning, and real-time data analytics. These gaps present opportunities for future research to develop more adaptive, data-driven models that can address real-world healthcare environments' complex, dynamic nature. Additionally, the review underscores the need for further exploration of sustainability in OR scheduling, offering a rich avenue for academic inquiry into eco-friendly and resource-efficient healthcare practices. This research can significantly contribute to refining theoretical models and enhancing their applicability across diverse healthcare contexts.

### (ii) Practical Implications.

On the practical side, the findings of this review offer valuable insights for healthcare managers and practitioners. The integration of optimization techniques and advanced technologies can improve OR scheduling efficiency, reduce waiting times, and optimize resource utilization. Hospitals can enhance operational performance and patient outcomes by addressing the uncertainty in surgical durations and patient arrivals. Moreover, sustainability-focused strategies identified in this study, such as minimizing energy consumption and reducing medical waste, provide practical steps toward more environmentally friendly and cost-effective operations. Implementing these solutions in real-world settings can lead to more resilient, efficient, and sustainable healthcare systems.

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**Data availability** The authors confirm that the data supporting the findings of this study are available within the article and/or its supplementary materials.

## Declarations

**Conflict of interest** The authors have no competing interests to declare that are relevant to the content of this article.

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