Computers & Operations Research 180 (2025) 107063

Contents lists available at ScienceDirect

Computers and Operations Research

journal homepage: www.elsevier.com/locate/cor

Survey in Operations Research and Management Science

Integration of decision levels in operating room scheduling problems: Systematic review and proposition of a decision support framework

Igor Eduardo Santos de Melo *, Flavio Sanson Fogliatto

Industrial Engineering Department, Federal University of Rio Grande do Sul, Av. Osvaldo Aranha, 99, 5th Floor, Porto Alegre 90035-190, Brazil

ARTICLE INFO

Keywords:
Resource allocation problems
Operating room planning and scheduling
Multiple decision level integration
Mathematical programming models
Systematic literature review

ABSTRACT

Resource allocation problems are a significant subset of optimization problems widely present in the healthcare industry. Notably, the Operating Room Scheduling Problem (ORSP) is prominent in literature due to its substantial cost and revenue implications. ORSP is structured into three hierarchical decision levels: strategic, tactical and operational, with higher-level decisions influencing subsequent ones. While most studies focus on single decision levels, there has been a growing interest in integrated models, as these offer a more holistic view and often result in better outcomes, despite their complexity of resolution. Although various literature reviews have explored different aspects of ORSP, few have focused on models integrating multiple decision levels. This study addresses that gap by systematically reviewing the literature focusing on contributions presenting mathematical programming models and optimization algorithms that simultaneously address multiple decision levels of the ORSP. Following the PRISMA 2020 protocol, the review spans works published until October 2024, totaling 46 articles. It outlines objectives, characteristics, solution approaches, and identifies gaps in literature. Additionally, a decision framework summarizing the identified integration levels is proposed.

1. Introduction

In the optimization field, key challenges in healthcare systems are related to scheduling activities, with emphasis on surgery scheduling, nursing rostering and bed allocation problems (Abdalkareem et al., 2021). The Operating Room Scheduling Problem (ORSP) is a combinatorial problem that allocates resources and patients to Operating Rooms (ORs) and is important since it generates significant financial resources while incurring high operational costs (Gür and Eren, 2018). The mean cost per minute of OR is estimated at \$36–37 (Childers and Maggard-Gibbons, 2018). Conversely, OR operations account for 40 to 70 % of hospital revenues (Doebbeling et al., 2012). In this context, managing the ORSP has the potential to enhance service quality, while dealing with resource constraints, stakeholder preferences and its NP-Hard nature (Abdalkareem et al., 2021; Rahimi and Gandomi, 2021).

ORSP reviews can be categorized as broad or focused in scope. Broad scope reviews (Harris and Claudio, 2022; Abdalkareem et al., 2021; Gür and Eren, 2018; Zhu et al., 2019; Samudra et al., 2016) provide an overview of the ORSP, categorizing literature according to various aspects, including decision levels. Abdalkareem et al. (2021), in particular, also address other hospital scheduling problems. Focused scope reviews analyze specific ORSP features, presenting discussions on modeling challenges, and insights into solution methods as well as future research trends. Focused reviews may be categorized into three groups: (i) those dealing with system-specific features, such as elective and non-elective patients (Van Riet and Demeulemeester, 2015) or patients requiring post-surgical hospitalization (Wang et al., 2021); (ii) those dealing with decision-making at different levels, e.g., tactical (Razali et al., 2022) or strategic (Hof et al., 2017); and (iii) those focusing on solution approaches, e.g., stochastic optimization (Shehadeh and Padman, 2022) or simulation-based approaches (Soh et al., 2017).

Regardless of the different scopes, an identified trend is the proposition of more holistic models to improve operational performance, considering different hospital resources (e.g., the Intensive Care Unit), hierarchical decision levels and correlated problems (Gür and Eren, 2018; Zhu et al., 2019; Wang et al., 2021; Samudra et al., 2016). Integrating decision levels allows examining their interdependence, enabling simultaneous adjustments across the planning horizon based on hospital capabilities (Guerriero and Guido, 2011; Agnetis et al., 2012). Such integrations support more flexible operational planning (Wang et al., 2021) and allow for the anticipation and adjustment of decisions over time, a key priority for hospital managers seeking stable

* Corresponding author.
E-mail addresses: igor.eduardo@ufrgs.br (I.E.S. Melo), ffogliatto@producao.ufrgs.br (F.S. Fogliatto).

https://doi.org/10.1016/j.cor.2025.107063
Received 23 May 2024; Received in revised form 27 January 2025; Accepted 16 March 2025
Available online 29 March 2025
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and adaptable long-term plans (Agnetis et al., 2012).

Studies in the literature demonstrate that integrated planning leads to more efficient outcomes. They show that by allowing small adjustments to previous (higher-level) decisions when defining current ones, service levels can be improved. This approach results in a higher number of patients treated, a reduction in late cases, improved OR utilization and overall improvements in patient waiting times and delays (Agnetis et al., 2012; Anjomshoa et al., 2018; Oliveira et al., 2022). However, despite its importance, the topic has not been explored in previous reviews. To the best of our knowledge, Guerriero and Guido (2011)'s investigation on mixed decision level models is the only exception. While their discussions on the topic provide valuable insights, a deeper investigation into possible integrations of ORSP decision levels, their motivations and benefits are still lacking in the literature.

Our research aims to bridge this gap by conducting a systematic literature review (SLR) on studies focusing on ORSP models that address more than one decision level, either sequentially or in an integrated manner. It highlights the studies' main characteristics, their mathematical models and solution methods, and proposed directions for future research. Our review study contributes to the state-of-the-art on the ORSP problem by clearly classifying the integrations found in the literature, expanding on the discussions of Guerriero and Guido (2011) regarding mixed decision level models and identifying research gaps. Additionally, a decision framework is proposed exploring the relationship between decision levels, uncertainty and planning horizons.

2. ORSP decision levels

The ORSP can be decomposed into three decision levels, namely strategic, tactical and operational. At the strategic level, decisions revolve around the quantity and types of surgeries to be performed in the long term, aiming to align the Surgical Theater's (ST) operations with organizational objectives (Samudra et al., 2016; Hans and Vanberkel, 2012). Based on the anticipated aggregate demand for surgeries, three decisions constitute the strategic level: (i) Capacity Planning Problem (CPP), which determines the amount of resources required to meet the demand; (ii) Case-Mix Problem (CMP), which selects the mix of surgeries offered and the volume of patients served per specialty to align with the hospital's financial and non-financial objectives; and (iii) Capacity Allocation Problem (CAP), which allocates OR times to specialties to meet the anticipated aggregate demand from patients, connecting decisions from CPP and CMP (Rahimi and Gandomi, 2021; Zhu et al., 2019; Hof et al., 2017).

At the tactical level, the ORSP is known as Master Surgery Scheduling (MSS), aimed at developing a monthly or quarterly plan (Blake et al., 2002a; Blake et al., 2002b). The plan specifies specialties or surgeons that will use the available ORs (Zhu et al., 2019; Wang et al., 2021). The MSS allows the prediction of total surgeries performed through a recurring specialty assignment, promoting workload balancing and resource utilization while simplifying operational scheduling (Zhu et al., 2019; Razali et al., 2022). In the Block Scheduling policy, time blocks are assigned to surgeons based on strategic-level decisions, resulting in a schedule of surgeons' activities in ORs. In the Open Scheduling policy, there is no allocation to specific time blocks, and surgeons compete for the ORs (Blake et al., 2002a). In this context, the allocation of surgeons and patients occurs simultaneously.

At the operational level, the ORSP is named Surgery Scheduling Problem (SSP), comprising two decisions: (i) surgical case allocation with a defined date for each operation (Advanced Scheduling) and (ii) surgical case scheduling with the exact start time of operations (Allocation Scheduling) (Rahimi and Gandomi, 2021; Zhu et al., 2019). Initial investigations into the ORSP during 1950–1960 focused on SSP (Magerlein and Martin, 1978; Przasnyski, 1986), while recent research addresses both decisions simultaneously (e.g., Al Hasan et al., 2019, 2024). These decisions form the offline SSP, typically involving weekly plans (Cardoen et al., 2010; Essen et al., 2012). Actual execution can vary due to uncertainties such as non-elective surgeries or patient no-shows (Erdem et al., 2012; Van Riet and Demeulemeester, 2015; Ballestín et al., 2019; Shehadeh and Padman, 2022). To manage uncertainties and obtain a feasible plan, the Rescheduling Problem reallocates patients to alternative time blocks or to different days (Samudra et al., 2016; Gür and Eren, 2018; Ballestín, et al., 2019).

The online SSP aims to control the process in real-time, responding to variability and preventing inefficient resource use. The decisions include reassignment, cancellations, overtime utilization (Duma and Aringhieri, 2015) and managing non-elective patient no-shows (Erdem et al., 2012). These ORSP subproblems are hierarchically organized in Fig. 1.

3. Methodology

This study reports a SLR aiming to identify, classify and summarize the literature on the integration of ORSP decision levels. The protocol used is the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 (Page et al., 2021), which guides the selection and assessment of studies. PRISMA imprints methodological rigor and reduces biases in article identification and evaluation, ensuring a transparent and reproducible study (Sohrabi et al., 2021). The State of the Art through Systematic Review (StArt) software (Fabbri et al., 2013) supported the organization of articles. The review is not registered in any specialized database.

The PRISMA protocol is operationalized as follows. First, research questions (RQ), databases and search terms are defined. Research is then conducted in the selected databases, followed by a preliminary selection. Next, articles are assessed by title, abstract and full text, and relevant information is collected and organized. The protocol concludes with the cross-referencing step. The PRISMA checklist is given in Appendix B. The first three steps of the PRISMA protocol are detailed next.

3.1. Research questions, databases and search terms

The following RQs were proposed: (RQ1) *What existing literature on the ORSP addresses different decision levels?*, (RQ2) *What are the objectives and main characteristics of the proposed models?*, (RQ3) *What solution*

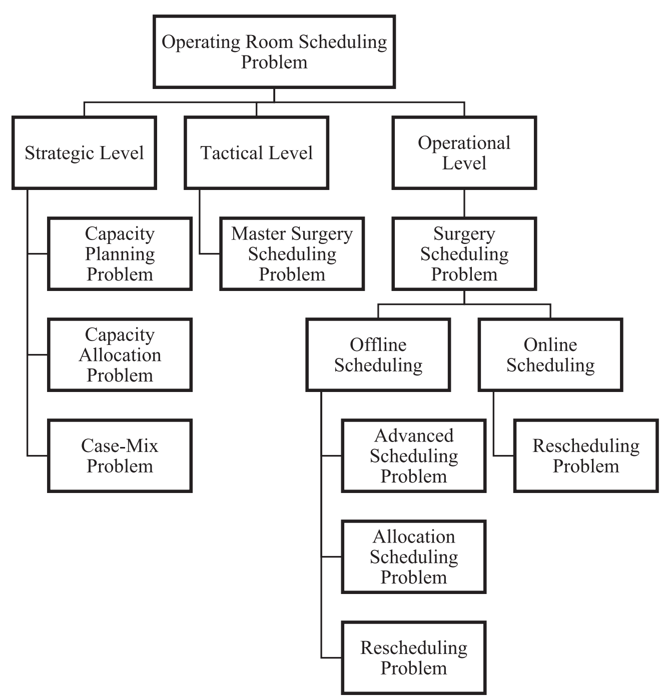

Fig. 1. Hierarchy of subproblems within the ORSP
Source: Adapted from Rahimi and Gandomi (2021).

approaches have been applied?, (RQ4) *What are the gaps in literature for future research?*

The search was conducted on the Web of Science, PubMed, Springer and Scopus databases. They cover a wide range of health and engineering journals and were used in previous ORSP reviews. The selected keywords reflect the main terms associated with the ORSP problem and decision levels, organized into four groups. Group 1 includes terms related to the surgical unit. Groups 2, 3 and 4 include keywords related to tactical-operational levels, strategic-operational levels and strategic-tactical levels, respectively (see Table 1 for details).

3.2. Search and preliminary selection of articles

The initial screening of articles used the following inclusion criteria: (i) the article addresses the ORSP problem, (ii) it was published between January 2002 and October 2024 and (iii) it was written in English. These criteria were applied directly within the databases. Grey literature, including conference papers, book chapters, government reports, theses, and dissertations, was excluded, representing a limitation of this review. While such sources could provide valuable insights and contribute to a more comprehensive understanding of the evidence (Paez, 2017), the focus was placed on peer-reviewed articles to ensure rigor and guarantee the quality of the findings. The search strategy is presented in Table 1. A total of 488 articles were identified, and 464 remained after removing duplicates. They were entered into StArt, considering title, keywords, abstract, year of publication, authors and journal information.

3.3. Analysis and final selection of articles

At this step, the authors analyzed and selected the articles. When there was no consensus on whether to include an article, a third-party expert (non-author) in the area was consulted, and the final decision was made by majority vote. Fig. 2 describes the review protocol process.

The initial assessment was based on the abstract, keywords and objectives (Group 1), with all inclusion questions required to be answered affirmatively. Next, the remaining articles were subjected to a full-text reading (Group 2). A sample of 34 articles was initially selected. Subsequently, a snowballing search was conducted using the reference lists of these 34 articles, checking and identifying additional relevant papers not included in the initial search (Wohlin, 2014). As a result, 12 new articles were added, leading to a final sample of 46 articles included in the review. Fig. 3 presents the systematic review flowchart. Appendix C details the search strategy applied.

4. Results

The selected articles were tabulated based on title, author, publication year, country, journal and the RQs addressed. An overview of the results is provided in section 4.1, addressing RQ1, while sections 4.2, 4.3 and 4.4 describe the articles in relation to RQ2 and RQ3. Appendix D summarizes the main characteristics of the articles reviewed in this section.

Table 1
Search strategy in databases.

Base	Fields	Search[a]
Web of Science, PubMed, Springer and Scopus	**Year of publication:** 2002 – 2024	**Group 1:** "*Operating Theater**" **OR** "*Operating Room**" **Group 2:** "*Surger* Schedul**" **AND** "*Master Surger**"
	Language: English	**Group 3:** "*Surger* Schedul**" **AND** ("*Case-Mix*" **OR** "*Capacit* Allocation*" **OR** "*Capacit* Plan**")
	Types of documents: research and review articles	**Group 4:** "*Master Surger**" **AND** ("*Case-Mix*" **OR** "*Capacit* Allocat**" **OR** "*Capacit* Plan**") **Search string:** All fields – Group 1 **AND** (Group 2 **OR** Group 3 **OR** Group 4)

[a] The character * is used to represent various forms of root words, including both singular and plural forms.

4.1. Descriptive analysis

The following analyses were conducted using the bibliometrix tool (Aria and Cuccurullo, 2017). Fig. 4 summarizes relevant information about the 46 selected articles.

Fig. 4a presents the biannual evolution of publications, with approximately 79 % published between 2015 and 2024. There are two output peaks (2015–2016 and 2021–2022), indicating recent interest in the topic. The articles were published in 22 journals, and the most prominent are listed in Fig. 4b; they are: Annals of Operations Research (Impact Factor, IF = 4.8), Health Care Management Science (IF = 3.6), Operations Research for Health Care (IF = 2.1), Computers & Operations Research (IF = 4.6), Computers & Industrial Engineering (IF = 7.9) and European Journal of Operational Research (IF = 6.4).

The first study on strategic-tactical integration was published in 2007 (Testi et al., 2007), while tactical-operational integration was first addressed in 2009 (Testi and Tànfani, 2009), both in Health Care Management Science. Most of articles (58.70 %, n = 27) focus on tactical-operational integration. The most cited article on strategic-tactical integration is Testi et al.'s (2007) (201 citations) and on tactical-operational integration is Aringhieri et al.'s (2015) (107 citations). Fig. 4c presents the most productive authors, with more than one published work, highlighting authors from Portugal (e.g., I. Marques), Italy (e.g., E. Tànfani) and Iran (e.g., K. Kianfar). Moreover, the authorship of most of the identified articles is concentrated in Europe (54.35 %, n = 25 articles), mainly in Italy, Portugal and Belgium (see Fig. 4d, which presents the articles stratified by the country of the Corresponding Authors). Only 22 authors participated in 2 or more studies. In total, 13 articles involve authors from multiple nationalities, with notable collaborations between Italy and Canada (Aringhieri et al., 2015, 2022) and Iran and India (Eshghali et al., 2023; Arab Momeni et al., 2022). However, the small number of international collaborations suggests fragmented scientific cooperation, potentially driven by region-specific hospital needs.

4.2. Integration of strategic, tactical and operational levels

The strategic-tactical-operational ORSP is denoted as Multi-Level Operating Room Planning and Scheduling (MLORPS) (Roshanaei et al., 2020) and involves (i) OR time allocation for specialties, (ii) OR time block allocation to surgeons/specialties and (iii) scheduling of surgeries. The usually weekly plannings share similarities with fully flexible tactical-operational models (Agnetis et al., 2012) that sacrifice planning stability to enhance operational performance.

MLORPS literature is dominated by Integer Linear Programming (ILP) models with multi-objectives. To handle large instances, population-based algorithms such as Genetic Algorithm (GA) (Marques et al., 2014), Evolutionary Algorithm (EA) (Marques and Eugénia Captivo, 2015) and Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Lu et al., 2019) have been dominant. Exact algorithms also have been explored (Castro and Marques, 2015; Roshanaei et al., 2020), with emphasis on Roshanaei et al. (2020)'s Branch-and-Check (B&C), which has outperformed Marques et al. (2014)'s GA in solution quality and computational time. Recently, hybrid approaches combining Gray Wolf Optimization (GWO) with Variable Neighborhood Search (VNS) algorithms (Zhu et al., 2020) have demonstrated superior efficiency and convergence speed over popular algorithms such as GWO, VNS and Particle Swarm Optimization (PSO). Despite their potential, hybrid heuristic strategies (e.g., Matheuristics, Hyper-heuristics) are underexplored in MLORPS.

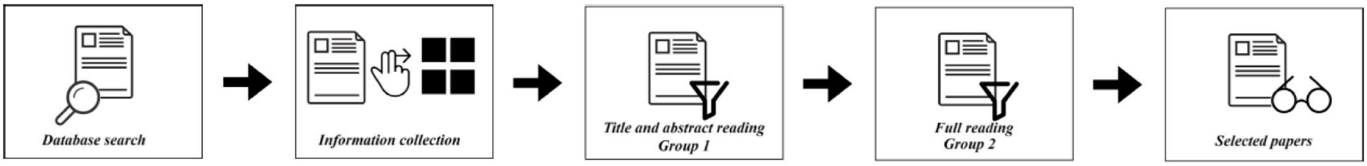

Fig. 2. Review protocol process.

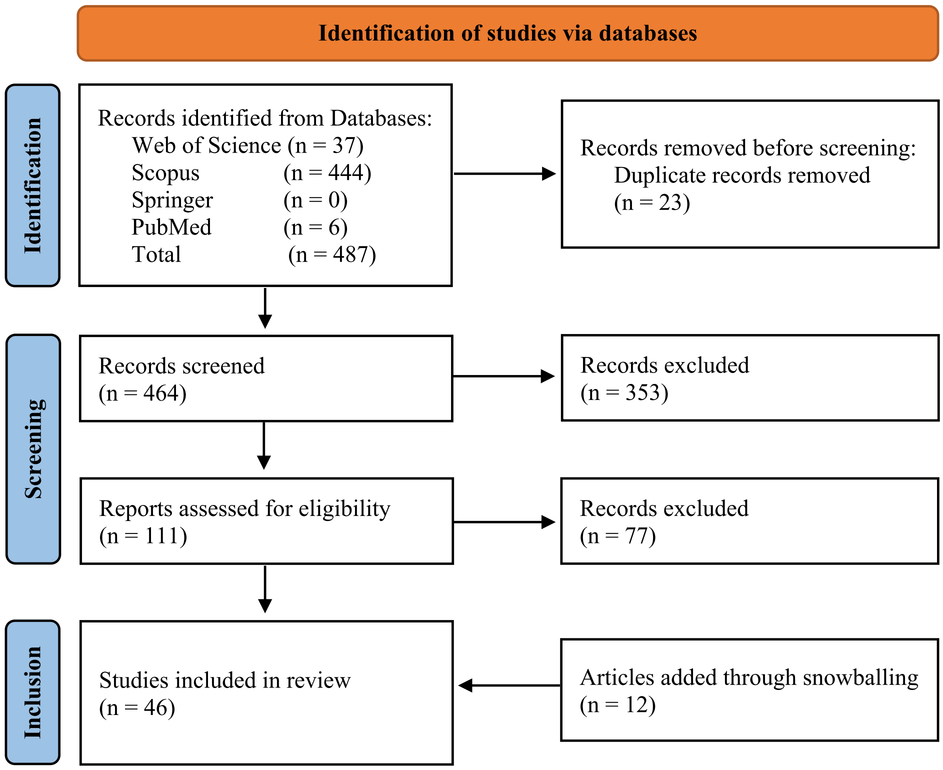

Fig. 3. Systematic review flowchart
Source: Adapted from Page et al. (2021).

Proposed objectives mainly focus on maximizing OR occupancy and the number of patients treated (Marques et al., 2012, 2014, 2015; Castro & Marques, 2015; Marques and Eugénia Captivo, 2015; Lu et al., 2019; Roshanaei et al., 2020), being tied to hospital efficiency and reflecting typical operational management priorities. A few authors examined conflicting objectives, such as minimizing patient hospitalization time and OR overtime costs (Zhu et al., 2020) and maximization of profits and minimization of OR utilization costs (Lu et al., 2019). Although MLORPS decisions are not typically financially driven, their findings revealed that a slight profit reduction could decrease overtime and increase OR utilization. However, further research is needed to explore how balancing financial and non-financial strategic goals with patient and surgeon preferences impacts hospital outcomes at this mixed decision level.

Operational scheduling constraints, such as patient conflicts and priority, OR availability and cleaning time are common in models (Marques et al., 2012, 2014, 2015; Roshanaei et al., 2020). Surgeon-related constraints (i.e., tactical level) are also often addressed, e.g., one specialty per OR, surgeon availability and working time limits per surgeon (Marques et al., 2012, 2014, 2015; Zhu et al., 2019; Roshanaei et al., 2020). A minimum service level was introduced by Lu et al. (2019) through lower bound time limits for specialties. However, bound levels for strategic managerial goals are not considered in literature (e.g., minimum profit or maximum cost acceptable), reaffirming the problem's limited financial focus.

MLORPS models provide decision-makers with a holistic view, allowing them to adjust strategies based on the specific needs of each week in the OR. However, in most studies, performance evaluation is based on the hospital's planning, often obtained by non-formal decision models. More studies are needed to verify the superiority of this integration over other less flexible integrations (e.g., tactical-operational models with limited changes in decisions over time). Similarly, studies could be conducted to assess the impact of the ongoing use of MLORPS on long-term organizational goals.

4.3. Integration of strategic and tactical levels

The strategic-tactical ORSP allocates OR time blocks to specialties and assigns surgeons or surgical teams to OR blocks. Typically, strategic decisions are set for the long run and tactically adjusted to accommodate resource fluctuations. A sequential approach breaks the problem into steps across different planning horizons. Usually, strategic decisions are treated as inputs to tactical models, which reduce their complexity. An integrated approach introduces flexibility in allocation, responding to uncertainties by leveraging supply and hospital demand, potentially enhancing service levels and revenues and reducing variability in surgeries and downstream resource demand spikes.

Both approaches are mainly modeled as Mixed-Integer Programming (MIP), and optimization could be computationally expensive even for medium-sized hospitals (Ma and Demeulemeester, 2013). To address such complexity, sequential frameworks have gained popularity. Testi

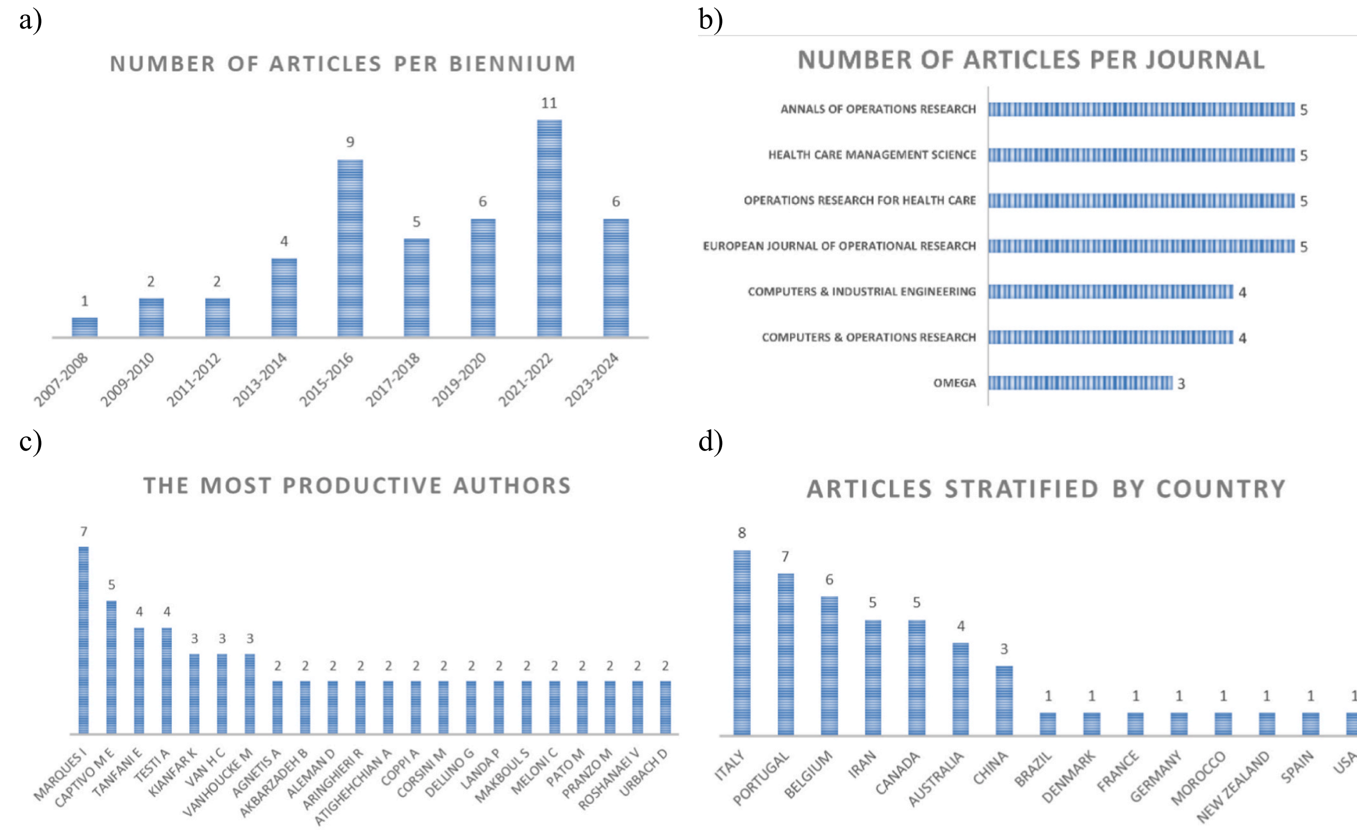

Fig. 4. Quantitative analysis of studies in the corpus.

et al. (2007) proposed a framework that solves each decision level once, while Ma and Demeulemeester (2013) introduced an iterative level-by-level approach that allows feedback and adjustments across phases, enhancing planning efficiency. Freeman et al. (2018) divided the strategic model into three stages, optimizing and re-optimizing the decisions. Next, an MSS is created and evaluated through simulation scenarios. Barafkandeh et al. (2022) also used an adaptive approach, solving a medium-term planning problem and reoptimizing decisions weekly based on real-time demand. On the other hand, few papers addressed heuristic algorithms. Oliveira et al. (2022) proposed a rolling horizon approach to evaluating management policies in a strategic-tactical plan. Yang et al. (2022) introduced a VNS algorithm to address instances presented by Anjomshoa et al. (2018) and Kianfar and Atighehchian (2023) proposed a matheuristic algorithm combining the Simulated Annealing (SA) metaheuristic with a simplified version of their MIP model.

Simulation techniques are highlighted by Testi et al. (2007), Ma and Demeulemeester (2013), Freeman et al. (2018) and Oliveira et al. (2022) as suitable for managing process uncertainty. Testi et al. (2007) explore how waiting list management strategies influence operational planning, while the other authors use simulation to gather insights and reoptimize decisions through feedback processes. Alternatively, some studies incorporate uncertainty into the models. Fügener (2015) proposed a Stochastic Optimization (SO) model to address uncertainty in available downstream beds. Marques et al. (2019) used random variables to capture the surgery duration uncertainty, while Barafkandeh et al. (2022) modeled uncertain surgical demand by Robust Optimization (RO).

Revenue maximization is the main objective when mixing strategic and tactical levels (Ma and Demeulemeester, 2013; Fügener, 2015; Anjomshoa et al., 2018; Freeman et al. 2018; Patrão et al. 2022; Yang et al. 2022). Hof et al. (2017) and Fügener (2015) argue that such objective can help hospitals financially and create a competitive advantage, but may also lead to service shortages and delayed patient care. For these reasons, constraints and objectives are introduced to maintain minimum service levels, such as setting bounds on patient group volume (Ma and Demeulemeester, 2013; Fügener, 2015) or minimizing waiting list size and reducing the number of overdue and canceled surgeries (Anjomshoa et al., 2018; Yang et al., 2022; Freeman et al. 2018).

Tactical objectives focus on efficient and balanced resource utilization, such as minimizing OR idle/overtime costs (Barafkandeh et al., 2022; Kianfar & Atighehchian, 2023), expected bed shortage (Ma and Demeulemeester, 2013) and variability in downstream resources (Freeman et al., 2018; Marques et al., 2019). Other common objectives are to aximize surgeons' allocation preferences (Testi et al., 2007; Barafkandeh et al., 2022; Kianfar & Atighehchian, 2023) and control long-term changes in surgical planning (Anjomshoa et al., 2018; Marques et al., 2019; Oliveira et al., 2022; Yang et al., 2022). Prioritizing preferences increases staff satisfaction and reduces stakeholder conflicts, while minimizing changes ensures stable and predictable plans that benefit supporting services. The balance between efficiency and stability has been successfully demonstrated by Marques et al. (2019) and Oliveira et al. (2022).

Regarding managerial insights, Anjomshoa et al. (2018) discussed that minimizing the waiting list favors surgeries with fewer resource demands. Conversely, prioritizing the reduction of overdue patients emphasizes meeting patient deadlines, giving a lower focus on resource requirements. Such prioritization may increase resource consumption and contribute to the growth of the waiting list. Patrão et al. (2022) noted that reducing patient wait times might increase resource costs (e.g., extra shifts), while lowering costs negatively affects patient waiting times. Kianfar and Atighehchian (2023) identified that increasing scheduled overtime reduces unscheduled surgeries, thereby improving the ability to meet demand, while greater idle time results in more unscheduled cases.

Strategic decisions influence not only financial outcomes but also directly affect hospital resource allocation (Fügener, 2015; Patrão et al., 2022). Strategic-tactical models help align long-term goals with medium-term surgical planning, improving hospital efficiency and reducing waiting times, particularly when plans are adjusted over time. Even minor adjustments to previous plans can enhance hospital performance (Anjomshoa et al., 2018; Oliveira et al., 2022).

4.4. Integration of tactical and operational levels

The tactical-operational ORSP involves the allocation of surgeons/specialties to time blocks and scheduling surgeries. Sequential and integrated approaches are used to address the problem. The sequential approach tackles levels separately, enabling faster solution convergence (Agnetis et al., 2014). However, making decisions at different times can cause misalignment between capacity and demand due to uncertainties, such as variations in surgical times and patient arrivals (Akbarzadeh et al., 2019; Makboul et al., 2022), leading to suboptimal plans as tactical decisions are not revised (Van Huele and Vanhoucke, 2015a; Mazloumian et al., 2022). Alternatively, the integrated approach simultaneously analyzes tactical and operational decisions to find an optimal plan, often at a higher computational cost (Spratt and Kozan, 2016; Moosavi and Ebrahimnejad, 2020).

The literature is mainly modeled by MIP, including linear (e.g., Aringhieri et al., 2022; Mazloumian et al., 2022) and non-linear variations (e.g., Spratt and Kozan, 2016). However, given the short time horizon of this mixed decision level, fast planning approaches are preferred for analyzing multiple scenarios and alternative OR schedules (Agnetis et al., 2014). As alternatives, (meta)heuristics (Tànfani and Testi, 2010; Aringhieri et al., 2015; Van Huele and Vanhoucke, 2015b; Guido and Conforti, 2017; Mashkani et al., 2023), Column Generation (CG) algorithms (Wang et al., 2018; Akbarzadeh et al., 2019; Ghandehari and Kianfar, 2022) and Benders Decomposition (Roshanaei et al., 2017) have been proposed to solve large instances efficiently. Additionally, hybrid approaches, such as combining metaheuristic algorithms (Spratt and Kozan, 2016; Spratt and Kozan, 2021), exact and heuristic methods (Moosavi and Ebrahimnejad, 2020; Aringhieri et al., 2022) and predictive and heuristic algorithms (Eshghali et al., 2023), also gained attention for balancing computational efficiency with solution quality, achieving better results than traditional (meta)heuristic methods.

Simulation-based approaches have received limited attention, being applied only by Van Huele and Vanhoucke (2015a) to evaluate the performance of integrated and interactive models across various instances and assess the impact of patient rejection policies on system performance. In contrast, SO and RO approaches have been widely explored, addressing uncertainties related to emergency arrivals, surgical durations, patient length of stay, downstream resource availability and demand fluctuations (Moosavi and Ebrahimnejad, 2020; Arab Momeni et al., 2022; Makboul et al., 2022). Results showed that minor degradations in deterministic solutions could ensure robust outcomes, producing plans that are resilient to unforeseen and extreme scenarios.

The main objective modeled is patient satisfaction, represented by minimizing waiting times and maximizing clinical priority (Testi and Tànfani, 2009; Tànfani and Testi, 2010; Agnetis et al., 2012; Agnetis et al., 2014; Aringhieri et al., 2015; Spratt and Kozan, 2016; Roshanaei et al., 2017; Akbarzadeh et al., 2019; Spratt and Kozan, 2021; Aringhieri et al., 2022; Augustin et al., 2022; Arab Momeni et al., 2022; Eshghali et al., 2023; Mashkani et al., 2023). Management goals are also often considered, aiming to balance service quality with operational performance in multi-objective models. These include minimizing unmet demand (Van Huele and Vanhoucke, 2014; Van Huele and Vanhoucke, 2015a; Van Huele and Vanhoucke, 2015b), reducing resource utilization costs (Moosavi and Ebrahimnejad, 2020; Mazloumian et al., 2022; Mashkani et al., 2023) and maximizing the number of surgeries performed (Wang et al., 2018; Makboul et al., 2022). Tactical objectives (e.g., surgeons' preferences and workload allocation balance) have received little attention. They are addressed only by Aringhieri et al. (2015) and Mashkani et al. (2023), which focus on equitable allocation of ORs and downstream resources.

Several objective trade-offs have been studied. According to Aringhieri et al. (2022), maximizing inward bed leveling leads to high-quality solutions regarding the number of scheduled surgeries, while the reverse effect was not observed. In scenarios with uncertainty in surgical times, prioritizing bed leveling also yielded more robust solutions. Mashkani et al. (2023) showed that maximizing OR utilization increases patient waiting times, whereas prioritizing waiting times slightly reduces OR utilization. Similarly, Augustin et al. (2022) noted that patient prioritization improves scheduling quality without affecting OR occupancy. Akbarzadeh et al. (2019) reported that prioritizing surgical cases and minimizing patient waiting times affects the number of surgical cases treated but may result in more frequent schedule changes in the initial plan. Guido and Conforti (2017) noted that maximizing surgeries may lead to scheduling less critical procedures, which could compromise care quality. Conversely, prioritizing critical surgeries may reduce the overall number of procedures scheduled. These findings highlight the trade-offs between schedule stability, operational efficiency and patient satisfaction, emphasizing the need for hospital managers to balance stakeholders' objectives.

Constraints have been proposed to align with decision-making levels and hospital characteristics. Key constraints include surgery assignment, resource capacity (e.g., ORs, ICU, ward beds) and specialty/surgeon assignment to ORs. Many models also incorporate constraints on surgery duration, resource availability, limits of time blocks per surgeon and prioritizing emergency cases to improve resource use, accommodate surgeon preferences and ensure patient care. Van Huele and Vanhoucke (2014) analyzed the impact of surgery and physician constraints on OR overtime. They found that among surgery constraints, those related to time windows are the most influential, followed by those related to recovery beds. Among physician constraints, specific OR assignments and working hour limits significantly impact OR overtime, while the maximum number of surgeries per day has the least effect.

In short planning horizons, adjustments in previous decisions can improve OR efficiency or help reassess plans in response to unexpected events (Agnetis et al., 2014; Akbarzadeh et al., 2019; Mashkani et al., 2023). These changes may positively impact metrics such as patient waiting times (Aringhieri et al., 2015) and waiting list sizes (Spratt and Kozan, 2021). Addressing tactical-operational decisions concurrently poses a complex optimization challenge, especially in integrated models with a large number of variables and constraints (Ghandehari and Kianfar, 2022). However, minor adjustments in previous tactical decisions can enhance surgical plans and simplify management (Agnetis et al., 2014). Therefore, managing the frequency of decision reviews and their extent is key to maintaining a stable surgical plan and effectively managing decision complexity at this mixed decision level.

Appendix E summarizes findings from the literature on the impact of different decision level integrations across hospital metrics.

5. Discussion

The ORSP involves three hierarchical decision levels, each with distinct decisions and planning horizons. While the literature predominantly addresses single-level models (Aringhieri et al., 2015; Ghandehari and Kianfar, 2022), there is growing interest in mixed-level problems. Despite being more challenging to solve, these models provide a holistic view of the OR department, exploring dependencies between levels and the influence of prior decisions on subsequent ones (Moosavi and Ebrahimnejad, 2020; Mashkani et al. 2023). Such integrations enable aligning hospital capacity with surgical demand, using real-time information to achieve efficient plans (Ma and Demeulemeester, 2013; Zhu et al., 2020; Mazloumian et al., 2022). As highlighted in Appendix E, mixed-level models tend to deliver improved outcomes, e.g., higher total revenue (Anjomshoa et al., 2018) and number of patients treated (Agnetis et al., 2012; Van Huele and Vanhoucke, 2014; Oliveira et al., 2022) and decline in overdue patients and waiting times (Agnetis et al., 2012; Aringhieri et al., 2015; Anjomshoa et al., 2018; Oliveira et al., 2022).

The reviewed papers show a greater focus on tactical-operational integration, followed by strategic-tactical models. Although a clear justification for that was not identified in the literature, we hypothesize that it may be related to the daily variability in hospital resources and demand. Tactical-operational models typically cover shorter planning horizons (see Appendix D), where operational decisions are directly affected by uncertainties, e.g., patient demand and waiting lists. Conversely, strategic-tactical integration covers longer periods, leading to fewer disruptions from daily variations once uncertainties are aggregated. Consequently, tactical-operational decisions are more challenging for hospital managers. However, in recent literature, there has been a growing interest in the integration of strategic and tactical decision levels.

Integrating all three decision levels seems to be of little managerial interest due to the conflict between strategic and operational levels' planning horizons. Articles by Zhu et al. (2020) and Roshanaei et al. (2020) presented MLORPS models with weekly planning horizons. Consequently, strategic decisions are constantly reevaluated in the short term, potentially misaligning with long-term organizational goals. Additionally, waiting lists for specialties in long-term planning can lead to rework if scheduled too far in advance due to their dynamic nature (Guido and Conforti, 2017; Oliveira et al., 2022).

The findings in Appendix D indicate that block scheduling is the preferred management policy. Its stability, easier implementation and predictable planning contribute to improved patient flow and resource coordination (Spratt and Kozan, 2016; Moosavi and Ebrahimnejad, 2020; Spratt and Kozan, 2021). Conversely, the open scheduling policy lacks the same level of detail (Ghandehari and Kianfar, 2022), potentially increasing the complexity of resource management (Agnetis et al., 2014), setup times (Moosavi and Ebrahimnejad, 2020) and the risk of equipment damage during transportation as specialties rotate in ORs (Marques et al., 2014). The modified block scheduling policy balances the benefits of block and open scheduling (Kianfar and Atighehchian, 2023). Akbarzadeh and Maenhout (2024) found that using a hybrid approach reduces surgeon switching costs and maintains high operating room utilization and patient throughput. Despite its potential benefits, the policy is still underexplored in the literature, warranting further research to confirm its effectiveness against traditional methods, especially in mixed-level decision contexts requiring stability and flexibility.

In the open scheduling context, the distinction between decision levels is not clear and models are often classified as tactical-operational (Guerriero and Guido, 2011), as surgeon and surgery allocations to ORs are performed jointly (Zhu et al., 2019). However, our findings indicate that under open scheduling, medium-term tactical decisions involve allocating surgeons to work shifts in the OR, resembling the Physician Rostering Problem derived from the MSS (Spratt and Kozan, 2016). Literature indicates that tactical decisions also include shift planning (Akbarzadeh et al., 2019), which can reduce personnel costs and patient waiting times (Wang et al., 2018). Additionally, planning may involve allocating nursing teams and/or anesthesiologists to ORs, e.g., Akbarzadeh et al. (2019). However, some authors do not consider these resources as constraints on OR activities (Marques et al. 2012; Marques et al. 2014) and they are disregarded in simplified models.

Weekly planning horizons expandable to monthly horizons are typically used in strategic-tactical problems, justified by the size of the models and their solving complexity (Ma and Demeulemeester, 2013). To ensure stability, models can be solved for one week and replicated for subsequent periods, e.g., Patrão (2022). More flexible models allow for weekly adjustments (e.g., Marques et al., 2019) while minimizing changes to the MSS. In tactical-operational integration, short-term planning (typically weekly) is preferred, justified by hospitals' planning strategies (Mazloumian et al., 2022; Moosavi and Ebrahimnejad, 2020; Marques et al., 2012), the weekly change in patient profiles on waiting lists (Guido and Conforti, 2017) and the occurrence of unexpected events (Arab Momeni et al., 2022; Dios et al., 2015).

Deterministic models dominate the literature; however, process uncertainties pose challenges (Akbarzadeh et al., 2019), potentially altering parameters and making plans infeasible (Makboul et al., 2022). The uncertainties addressed include variations in surgical demand (Barafkandeh et al., 2022), surgery duration (Spratt and Kozan, 2016), elective and non-elective patient arrivals (Freeman et al., 2018; Arab Momeni et al., 2022), post-surgical ICU bed availability (Makboul et al., 2022) and patient length of stay in ward beds (Moosavi and Ebrahimnejad, 2020). Uncertainty is often addressed in tactical-operational models, followed by strategic-tactical models, in which RO (e.g., Mazloumian et al., 2022) and SO approaches (e.g., Wang et al., 2018) are dominant. The RO provides fewer conservative solutions by accepting uncertainty without requiring consideration of every possible scenario (Arab Momeni et al., 2023). Although SO models address uncertainty more comprehensively, they require extensive data and computational resources (Moosavi & Ebrahimnejad, 2020; Mazloumian et al., 2022), making it less practical for tactical-operational models with shorter planning horizons, where time for decision-making is limited (Makboul et al., 2024).

In OR planning, constraints related to downstream resources are predominant (e.g., ICU beds as in Arab Momeni et al., 2022), followed by upstream resources (e.g., conventional preoperative beds as in Moosavi and Ebrahimnejad, 2020). Although constraints related exclusively to ORs are commonly addressed, this may result in unfeasible or suboptimal surgical plans (Moosavi and Ebrahimnejad, 2020), uncoordinated with other departments (Arab Momeni et al., 2022). Leveling the upstream and downstream resources can increase staff comfort and improve the quality and equity of patient care, beyond reducing the probability of rejecting emergency patients (Moosavi and Ebrahimnejad, 2020). Although downstream resources are often modeled in the literature (see Appendix D), only Oliveira et al. (2022) and Moosavi and Ebrahimnejad (2020) addressed both types of resources in strategic-tactical and tactical-operational planning, respectively. Given the importance of upstream resources in providing adequate pre-surgery care for certain patients, further studies are needed to explore their impact on various hospital efficiency metrics across mixed decision levels.

Literature explored various objectives in mixed level approaches, often through multi-objective models. This diversity arises from the preferences, conflicting or not, of the stakeholders involved, i.e., managers, surgeons and patients (Moosavi and Ebrahimnejad 2020; Aringhieri et al., 2022). Marques et al. (2014, 2015), Marques and Captivo (2015), Guido and Conforti (2017) and Aringhieri et al. (2022) showed that optimizing one objective can negatively impact others, resulting in inefficient plans. To address many preferences, approaches such as GP (Van Huele and Vanhoucke, 2015a), weighted sum (Dios et al., 2015), hierarchical optimization (Aringhieri et al., 2022) and heuristic algorithms (Marques et al., 2015) stand out.

Recent trends in mixed-level models have emerged, particularly an increase in strategic-tactical models (see Appendix D), improving the alignment between long and medium-term decisions. In this context, the increasing use of heuristic algorithms supports the analysis of multiple scenarios and enables faster plan adjustments (Oliveira et al., 2022; Yang et al., 2022; Kianfar and Atighehchian, 2023). Models have increasingly incorporated uncertainty parameters, particularly regarding surgery durations and emergency arrivals, with focus on non-elective patients (Freeman et al., 2018; Moosavi and Ebrahimnejad, 2020; Spratt and Kozan, 2021; Arab Momeni et al., 2022; Makboul et al., 2022; Mazloumian et al., 2022; Eshghali et al., 2023), reflecting a shift towards dynamic management of surgical plans. Hospitals often dedicate ORs exclusively for non-elective cases (Eshghali et al., 2023), leading to potential underutilization during low emergency demand periods. Alternatively, recent models proposed shared ORs for elective and non-elective patients, incorporating time buffers for emergencies (Freeman et al., 2018; Spratt and Kozan, 2021). However, the uncertainty of emergency arrivals necessitates careful estimation of buffer requirements, as inaccurate assessments can compromise the efficiency of plans (Arab Momeni et al., 2022; Mazloumian et al., 2022).

6. Proposed decision framework

The literature emphasizes that small changes in predefined surgery planning enhance service levels, but hospitals may react to adjustments differently (Agnetis et al. 2012). Understanding the ORSP decision levels and their relationships should assist hospitals in developing models tailored to their capabilities and requirements. Based on our findings, the different mixed-level problems were generalized and organized into a framework, shown in Fig. 5. The ORSP decision levels are characterized by planning horizon (i.e., long to short-term) and uncertainty level (i.e., low to high). As presented in section 2, at the strategic level, allocations are aggregated, while at the operational level disaggregation occurs, increasing the level of detail in surgical planning. Although uncertainty factors may increase as the planning horizon extends, we assume that aggregating these factors compensates the overall observed variability. Consequently, the degree of uncertainty (or rather its impact on plans) increases from the strategic to the operational level.

At each decision level in Fig. 5, we display the standard (baseline) decision and the integrations that may occur. We assume that integrations between two decision levels occur at the intersection of their respective planning horizons. The intersections, highlighted in gray, are denoted as mixed decision levels. Each intersection can be subdivided into two distinct sublevel integrations depending on the decision level in which they are positioned. The tactical level is part of all two-level integrations, which will therefore impact the design of MSSs in different ways. Moreover, a set of possible paths are highlighted. Solid arrows represent the conventional path, where decisions are defined and inherited without reassessment at subsequent levels. Dashed arrows represent alternative paths, where decisions are anticipated (e.g., strategic-tactical and tactical-operational level) and reevaluated (e.g., tactical-strategic and operational-tactical levels). In Fig. 5, adjustments to previously made decisions are emphasized in red to illustrate the reevaluation process across mixed decision levels. Appendix D provides a description of each article and its identified sublevel integrations. Our analysis moves from the strategic to the operational level.

In the proposed framework, strategic decisions interact with tactical decisions in three ways. First, strategic decisions can be inherited into the medium term, following a sequential approach. Second, tactical decisions can be integrated at the strategic level, resulting in long-term MSSs that enable surgical teams to organize schedules in advance, including activities outside the hospital (Freeman et al., 2018; Oliveira et al., 2022). That facilitates early conflict identification (Fügener, 2015) and supports optimization strategies, e.g., increasing staff in high-demand specialties (Patrão et al., 2022), guiding strategic decisions. Static long-term MSSs are common in teaching hospitals (Fogliatto et al., 2023), where surgeons balance teaching, supervision and private practice responsibilities. These MSSs are revised only after significant changes in demand or infrastructure. Finally, strategic decisions can be integrated at the tactical level, allowing for revisions or creation of MSS to account for variations in staff availability and OR capacity (Blake et al., 2002b), resulting in more efficient plans regarding waiting times and delays (Oliveira et al., 2022). Such revisions are important to maintain the balance between flexibility and stability (Oliveira et al., 2022; Marques et al., 2019). Of the 11 studies that focused on this integration, two addressed long-term MSSs, five examined flexible MSSs and four explored a combination of long-term MSSs with iterative reassessment.

The MSS table derived from long- or medium-term plans interacts with operational decisions in three ways. First, tactical decisions can be inherited in the short term, following a sequential approach. Incorporating operational decisions at the tactical level can benefit less static MSSs, allowing adjustments in medium-term horizons (e.g., from several weeks to one week). This adds greater detail, such as specific dates and surgery shifts. As a result, patients can be informed of their surgery dates in advance, improving communication and potentially reducing cancellations and no-shows (Dios et al., 2015). Third, integrating tactical decisions at the operational level is essential for generating feasible surgery schedules. Surgery scheduling usually covers short horizons (e.g., days to one week) and is sensitive to unpredictable events (e.g., no-shows and emergency surgeries) that can reduce efficiency. Revising these schedules relies on tactical-level information and may involve strategies such as block time release and rolling horizon approaches. Reassessing tactical decisions in this way improves resource utilization and helps manage the dynamics of waiting lists (Agnetis et al., 2012). Such reassessment can also influence the strategic level by adjusting the parameters that affect long-term MSS (e.g., Agnetis et al., 2012; Agnetis et al., 2014; Tànfani and Testi, 2010). Of the 24 articles focusing on the tactical-operational decision level, sixteen addressed incorporating operational decisions into the tactical level, two addressed responsive plans integrating tactical decisions into the operational level and six explored both approaches.

A special case of tactical decisions integrated into the operational level arises when previous strategic decisions are disregarded, resulting in a MLORPS approach, e.g., Marques et al. (2012) and Marques et al. (2014). Adding even more flexibility to the decision process at operational level is reasonable due to the high uncertainty level related to short-term planning. However, while better operational performance may be achieved, implementing strategic decision changes may not be easily achievable on a short-term horizon since they often result from

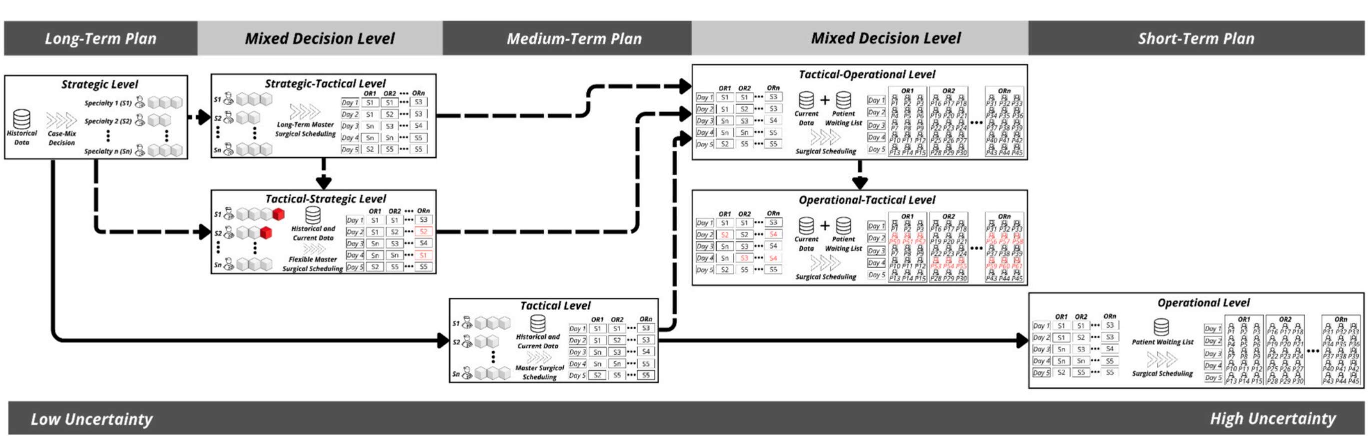

Fig. 5. Conceptual framework for the integration of ORSP decision levels.

negotiations involving multiple stakeholders (Aringhieri et al., 2015) and infrastructure investments. A total of 8 articles explored the MLORPS approach.

7. Conclusion and future research directions

The literature on healthcare optimization highlights the significance of optimization models for enhancing operational performance, minimizing waste and balancing stakeholders' preferences. The ORSP is particularly important due to its impact on surgical theater costs and revenues. In this paper, we report the results of a systematic literature review of studies focusing on mathematical models or optimization algorithms addressing two or more ORSP levels. Following the PRISMA 2020 protocol, 46 articles were chosen and categorized, and their objectives, features and solution methodologies were discussed. A decision framework was then proposed, classifying mixed-level models by uncertainty and planning horizon length.

Based on the selected articles, the following research gaps were identified and discussed below, addressing RQ4 through a future research agenda:

Integration of Multiple Decision Levels – while 83 % of the identified articles (38 out of 46) have addressed pairs of decision levels in ORSP, there remains a need for comprehensive models that integrate strategic, tactical and operational decisions for effective surgical scheduling and planning. As discussed in section 4.2, integrating all three levels can significantly enhance hospital performance, but the effects of varying management policies on these models remain unexplored. Replicating studies such as Oliveira et al. (2022) and Agnetis et al. (2012) could help determine whether similar findings apply to MLORPS models. Additionally, key strategic objectives, such as revenue maximization, have not been thoroughly investigated. Future research could examine the long-term consequences of prioritizing operational objectives over strategic ones and vice versa.

Integration of Strategic-Tactical Decision Levels – Although interest in strategic-tactical mixed-level models has grown, only 25 % of identified studies (3 out of 12 articles) proposed alternative algorithms capable of efficiently solving planning problems within reasonable timeframes. The development of heuristic algorithms remains a promising avenue for future research, as it could enable faster planning and support scenario analysis. Additionally, financial strategic objectives are often modeled in literature (6 out of 12 articles, or 50 %), while non-financial objectives have received comparatively less attention and were addressed in a more varied manner. Future research could investigate the role of non-financial objectives in fostering competitive advantages and their potential influence on a hospital's financial performance, especially for non-profit institutions.

Incorporation of Uncertainty and Non-Elective Patients – Most models focus on deterministic instances (30 out of 46 articles, or 65 %), neglecting the inherent uncertainties in surgical demand and duration, among other parameters. Future research should prioritize the development of simulation-based, stochastic and robust optimization models capable of addressing those uncertainties. Also, only 8 out of 46 articles (17 %) consider non-elective patients. Future studies could further investigate the impact of such patients on various hospital objectives and resources.

Consideration of Stakeholder Preferences – The literature reveals that surgeon preferences are often overlooked in the optimization process, typically modeled as constraints and featured as objective functions in only 9 % of the reviewed articles (4 out of 46 articles). Future research should prioritize developing models that better balance conflicting stakeholder objectives, particularly by more effectively integrating the preferences of surgeons and their teams.

Evaluation of Model Implementation and Benchmark Databases – while many studies propose optimization models for OR scheduling and planning, limited empirical evidence exists on their real-world implementation in long-term. Future research should focus on assessing the practical application of these models in hospitals, measuring their impact on key performance indicators. Additionally, most studies (40 out of 46 articles, or 87 %) rely on case studies or hospital databases. However, only a few (10 out of 46 articles, or 22 %) utilized previously published cases or shared instances online, which makes it difficult to assess the efficiency of algorithms across various settings. To promote the development of more efficient algorithms and greater reproducibility of results, public benchmark databases should be adopted.

Upstream Resources and Modified Block Strategy – While downstream resources are extensively considered in the literature (25 out of 46 articles, or 54 %, mainly in strategic-tactical and tactical-operational models), only 7 % (3 out of 46 articles) have addressed upstream resources, which are critical for providing adequate pre-surgical care. Future research should prioritize the integration of both upstream and downstream resources to assess their impact on hospital metrics. Additionally, most of the studies (39 out of 46 articles, or 85 %) adopt the block scheduling scheme. Future work could explore modified and open scheduling approaches, especially in mixed-level models, to offer valuable insights for hospital management.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Grammarly and ChatGPT 3.5 tools for translation and grammar revision. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

CRediT authorship contribution statement

Igor Eduardo Santos de Melo: Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Flavio S. Fogliatto:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This research was partially supported by the Coordination for the Improvement of Higher Education Personnel (CAPES) (process number = 88887.669940/2022-00) and the National Council for Scientific and Technological Development (CNPq) (process number = 141543/2024-8). Compliance with ethical standards.

Appendix A. – Abbreviations

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Abbreviation	Description
B&C	Branch-and-Check
CAP	Capacity Allocation Problem
CG	Column Generation
CMP	Case-Mix Problem
CPP	Capacity Planning Problem
EA	Evolutionary Algorithm
GA	Genetic Algorithm
GWO	Gray Wolf Optimization
ICU	Intensive Care Unit
IF	Impact Factor
ILP	Integer Linear Programming
MILP	Mixed-Integer Linear Programming
MIP	Mixed-Integer Programming
MLORPS	Multi-Level Operating Room Planning and Scheduling
MSS	Master Surgery Scheduling
NP-Hard	Non-deterministic Polynomial-time Hardness
NSGA-II	Non-dominated Sorting Genetic Algorithm II
OR	Operating Room
ORSP	Operating Room Scheduling Problem
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSO	Particle Swarm Optimization
RO	Robust Optimization
RQ	Research Question
RTM	Real Time Management
SA	Simulated Annealing
SO	Stochastic Optimization
SSP	Surgery Scheduling Problem
VNS	Variable Neighborhood Search

Appendix B. – PRISMA 2020 checklist

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Section and Topic	**Item#**	**Checklist item**	**Location where item is reported**
TITLE			
Title	1	Identify the report as a systematic review.	Pg. 1
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	Pg. 1
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Pg. 3
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Pg. 3
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	Pg. 8 and 44
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	Pg. 6–7
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	Pg. 7 and 44
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	Pg. 8
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	Pg. 6–8
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g., for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	Pg. 44
	10b	List and define all other variables for which data were sought (e.g., participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	Not applicable
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	Not applicable
Effect measures	12	Specify for each outcome the effect measure(s) (e.g., risk ratio, mean difference) used in the synthesis or presentation of results.	Not applicable
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g., tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	Not applicable

(*continued on next page*)

(*continued*)

Section and Topic	**Item#**	**Checklist item**	**Location where item is reported**
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	Not applicable
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	Not applicable
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If *meta*-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	Not applicable
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g., subgroup analysis, *meta*-regression).	Not applicable
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	Not applicable
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	Not applicable
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	Not applicable
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	Pg. 9
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	Not applicable
Study characteristics	17	Cite each included study and present its characteristics.	Pg. 45–47
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	Not applicable
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g., confidence/credible interval), ideally using structured tables or plots.	Not applicable
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	Not applicable
	20b	Present results of all statistical syntheses conducted. If *meta*-analysis was done, present for each the summary estimate and its precision (e.g., confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	Not applicable
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	Not applicable
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	Not applicable
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	Not applicable
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	Not applicable
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	Pg. 10–23
	23b	Discuss any limitations of the evidence included in the review.	Pg. 10–23
	23c	Discuss any limitations of the review processes used.	Not applicable
	23d	Discuss implications of the results for practice, policy, and future research.	Pg. 23–29
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	Pg. 6
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	Pg. 30
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	Not applicable
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	Not applicable
Competing interests	26	Declare any competing interests of review authors.	Pg. 30
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	Not applicable

Appendix C. – Detailed research strategy

The following subsections describe with more detail the research process, see Section 3 to an overview.

C.1. Search strings, filters applied and summary results

The search string is a combination of keywords from Groups 1, 2, 3, and 4. The search string combination was: Group 1 **AND** (Group 2 **OR** Group 3 **OR** Group 4). The inclusion criteria were applied directly in the databases (see Section 3). Conference proceedings and grey literature were excluded. The databases used, complete search string and a summary of the results can be visualized in Table C1.

C1. Details of the research process.

Database	Search string	Number of papers			
		Initial collect	After Removing Duplicates	After Content Analysis (Group 1)	After Content Analysis (Group 2)
WoS	(“Operating Theater*” **OR** “Operating Room*”) **AND** ((“Surger* Schedul*” **AND** “Master Surger*”) **OR** (“Surger* Schedul*” **AND** (“Case-Mix” **OR** “Capacit* Allocation” **OR** “Capacit* Plan*”)) **OR** (“Master Surger*” **AND** (“Case-Mix” **OR** “Capacit* Allocat*” **OR** “Capacit* Plan*”)))	37	25	5	4
Scopus		444	439	106	30
Springer		0	0	0	0
PubMed		6	0	0	0

C.2. Inclusion and exclusion criteria

The inclusion criteria (Group 1) required articles to meet all specified questions, while the exclusion criteria (Group 2) allowed articles to be included if they met at least one of the defined criteria. Group 1 focused on identifying studies that explicitly addressed ORSP problems and incorporated decision-making at different levels. The following eligibility questions were used in Group 1: (i) Is the focus of the article on optimization? (ii) Are different decision levels addressed? (iii) Is mathematical modeling and/or a solution algorithm explicitly discussed? Out of the 464 articles screened, only 111 papers (24 %) satisfied Group 1 criteria.

Group 2 consisted of questions designed to answer our research questions. Group 2 was screened based on the following eligibility questions: (i) Does the article present a definition for the integration of subproblems? (ii) Are the nature and characteristics of the studied hospital explicitly described? (iii) Are the advantages and limitations of the solution approach clearly presented? Of the 111 papers, only 34 (31 %) provided affirmative responses to at least one of the Group 2 questions.

Following the initial analysis, a snowballing procedure was employed to identify further relevant papers. A backward snowballing procedure (Wohlin, 2014) was applied to the reference lists of the 34 identified articles. An initial screening was conducted to exclude papers that did not meet the search strategy (see Section 3). Each remaining paper was then thoroughly evaluated based on the Group 1 and Group 2 criteria. This process led to the inclusion of 12 additional articles, bringing the final review sample to 46 articles.

Appendix D. – Description of studies reviewed

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Reference	Decision Level[1]	Sublevel[2]	Management Strategy[3]	Type of patient[4]	Objective[5]	Solution Approach Mathematical Model[6]	Solution Approach Proposed Algorithm[7]	Resources[8]	Planning Horizon[9]	Numerical Experiments[10]	Type of Stochasticity[11]
Marques et al. (2012)	1, 2, 3	4	1	1	1	1	1	–	1	1, 2	–
Marques et al. (2014)	1, 2, 3	4	1	1	1, 2	1	2	–	1	1, 2	–
Marques et al. (2015)	1, 2, 3	4	1	1	1, 2	1	1	–	1	1, 2	–
Marques and Captivo (2015)	1, 2, 3	4	1	1	1, 2	–	2	–	1	1, 2	–
Castro and Marques (2015)	1, 2, 3	4	1	1	1	–	3	–	1	1, 2	–
Roshanaei et al. (2020)	1, 2, 3	4	1	1	1, 2	1	3	–	1	1, 2, 3	–
Zhu et al. (2020)	1, 2, 3	4	1	1	3, 4	2	2	–	1	2	–
Lu et al. (2019)	1, 2, 3	4	1	1	2,4,5,6,7	1, 3	2	–	2	1	–
Testi et al. (2007)	1, 2	1	1	1	8, 9	1	–	–	1, 3	2	–
Ma and Demeulemeester (2013)	1, 2	1, 2	1	1	6, 10	1, 4	–	1	1, 3	3	1
Fügener (2015)	1, 2	1	1	–	6	4, 5	–	1	1, 3	2	2
Anjomshoa et al. (2018)	1, 2	2	1	1	6,11,12,13,14	4	–	1	1, 3	1	–
Yang et al. (2022)	1,2	2	1	1	6,11,12,13,14	4	2	1	1, 3	3	–
Marques et al. (2019)	1, 2	2	1	1	15,16,17,18	4	–	1	3	2	3
Oliveira et al. (2022)	1, 2	1, 2	1	1	19	4	1	1, 2	1, 3, 4	2	–
Patrão et al. (2022)	1, 2	1, 2	1	1	6, 20	1	–	1	1, 3	2	–
Barafkandeh et al. (2022)	1, 2	1, 2	1	1	4, 5, 9, 21	4, 6	–	1	1, 3	2	4
Freeman et al. (2018)	1, 2	2	1	1, 2	6,15,22,23	4	–	1	–	1	1, 2, 3, 5, 6
Kianfar and Atighehchian (2023)	1, 2	2	2	1	4, 5, 9, 21	1, 4	4	1	1, 3	1, 2	–
Akbarzadeh and Maenhout (2024)	1,2	1	1, 2, 3	1	9, 43, 44, 45, 46	4	–	–	3	2	–
Agnetis et al. (2012)	2, 3	3, 4	1	1	24	1	–	–	1	1	–
Agnetis et al. (2014)	2, 3	3, 4	1	1	24	1	–	–	1, 4	2	–
Testi and Tànfani (2009)	2, 3	3	1	1	25	7	–	1	1	2	–
Tànfani and Testi (2010)	2, 3	3	1	1	25	7	1	1	1	3	–
Aringhieri et al. (2015)	2, 3	3	1	1	25	7	2	1	1	1	–
Aringhieri et al. (2022)	2, 3	3	1	1	2, 15	4	4	1	1	3	–

(continued on next page)

(*continued*)

Reference	Decision Level[1]	Sublevel[2]	Management Strategy[3]	Type of patient[4]	Objective[5]	Solution Approach		Resources[8]	Planning Horizon[9]	Numerical Experiments[10]	Type of Stochasticity[11]
						Mathematical Model[6]	Proposed Algorithm[7]				
Mashkani et al. (2023)	2, 3	3, 4	1	1	26	4	1	–	1, 3	3	–
Augustin et al. (2022)	2, 3	3	1	1	1	4	–	1	1	2	2
Akbarzadeh et al. (2019)	2, 3	4	1	1	2,19,25,27	4	3	–	2	1, 2	–
Guido and Conforti (2017)	2, 3	3	1	1	2,4,5,28	1	2	–	1	1	–
Ghandehari and Kianfar (2022)	2, 3	3	1	1	4,25,29,30	4, 8	3	–	1	3	–
Moosavi and Ebrahimnejad (2020)	2, 3	3	1	1, 2	15,25,31	4, 6	2, 4	1, 2	1	2, 3	1, 3, 5
Makboul et al. (2022)	2, 3	3	1	1, 2	28	1, 6	–	1	1	1	2, 3
Mazloumian et al. (2022)	2, 3	3	1	1, 2	4, 5, 25, 32, 33	4, 5, 7	–	1	1	2	3, 5
Spratt and Kozan (2016)	2, 3	3	1	1	2	2	2	–	1	2	3
Spratt and Kozan (2021)	2, 3	3, 4	2	1, 2	28	4	1, 2, 5	–	1	1, 3	3, 5
Arab Momeni et al. (2022)	2, 3	4	1	1, 2	4, 5, 34, 35, 36, 37	4, 6	–	1	1	2	2, 3, 5
Eshghali et al. (2023)	2, 3	3, 4	1	1, 2	4, 25	1, 4	2	1	1, 2	1, 2	3
Roshanaei et al. (2017)	2, 3	3	1	1	25, 29	1	3	–	1	1	–
Makboul et al. (2025)	2, 3	4	1	1	25, 28, 40, 41	4, 6	6	1	1	1	1, 3
Manshadi (2024)	2, 3	4	1	1, 2	5, 10, 25, 26, 42	4, 5	1	1, 2	1, 3	2	1, 3
Van Huele and Vanhoucke (2014)	2, 3	3	3	1	4	3, 4	–	1	1	1	–
Van Huele and Vanhoucke (2015a)	2, 3	3	3	1	2, 4	3, 4	–	1	1	1	–
Van Huele and Vanhoucke (2015b)	2, 3	3	3	1	4,7,29,38	3, 4	1	1	1	1	–
Dios et al. (2015)	2, 3	3, 4	3	1	25, 28	4	1	–	1, 3	1, 3	–
Wang et al. (2018)	2, 3	3	3	1	39	5	3	–	1	2	3
Akbarzadeh and Maenhout (2024)	2,3	3, 4	1, 2, 3	1	17, 28, 47, 48	4	–	–	1	2	–

[1]Decision Level: 1) Strategic Level, 2) Tactical Level, and 3) Operational Level | [2] Decision Sublevel: 1) Strategic and Tactical Decisions, 2) Tactical and Strategic Decisions, 3) Tactical and Operational Decisions, 4) Operational and Tactical Decisions | [3] Management Strategy: 1) Block Scheduling, 2) Modified Scheduling, and 3) Open Scheduling | [4] Type of Patients: 1) Elective, and 2) Non-Elective | [5] Objective Function: 1) Maximize OR occupation, 2) Maximize surgeries scheduled, 3) Minimize hospitalization cost, 4) Minimize OR overtime, 5) Minimize OR underutilization, 6) Maximize total income, 7) Maximize balance OR occupation, 8) Maximize the marginal benefit of OR allocation, 9) Maximize surgeons' allocation preferences, 10) Minimize bed shortage, 11) Minimize overdue patients, 12) Minimize tardy days, 13) Minimize waiting list size, 14) Maximize the number of elective patients treated on time, 15) Minimize workload variability at downstream resources, 16) Minimize number of ORs allocated to each surgical specialty, 17) Minimize the surgeon's weekly OR time variability, 18) Minimize deviation between assigned and available surgical specialty shifts, 19) Minimize deviations from the base scale, 20) Minimize inappropriate ward bed allocation costs, 21) Minimize uncovered demand, 22) Maximize full-day block allocations, 23) Minimize elective patient cancellations, 24) Maximize total surgery score, 25) Minimize patient waiting time, 26) Minimize clinical condition deterioration, 27) Minimize staff reallocation, 28) Maximize patient priority, 29) Minimize OR opening cost, 30) Minimize Surgeon Idle Time, 31) Minimize workload variability at upstream resources, 32) Minimize postponed surgeries, 33) Minimize losses due to interruptions, 34) Minimize overtime worked by the surgeon, 35) Minimize idle time worked by the surgeon, 36) Minimize downstream overtime, 37) Minimize downstream idle time, 38) Minimize "as-soon-as-possible" scheduling costs, 39) Minimize total staffing costs, 40) Maximize workload balance, 41) Minimize assignment cost, 42) Minimize re-admitting patient cost, 43) Maximize adjacency of open blocks, 44) Minimize size differences between surgeon groups, 45) Minimize similarity between surgeon groups, 46) Maximize equitable block allocation among groups, 47) Maximize consecutive time blocks for a surgeon, 48) Minimize surgical schedule changes | [6] Mathematical Model: 1) Integer Linear Programming, 2) Mixed-Integer Non-Linear Programming, 3) Goal Programming, 4) Mixed-Integer (Linear) Programming, 5) Stochastic Optimization, 6) Robust Optimization, 7) Binary Linear Programming, and 8) Constraint Programming | [7] Proposed Algorithm: 1) Heuristic, 2) Metaheuristic, 3) Decomposition, 4) Matheuristic, 5) Hyper-heuristic, and 6) Exact algorithm | [8] Resources: 1) Downstream Beds, and 2) Upstream Beds | [9] Planning Horizon: 1) Weeks, 2) Days, 3) Months, and 4) Year | [10] Numerical Experiments: 1) Data Mimics Real Hospital, 2) Real Data, and 3) Generated Data | [11] Type of Stochasticity: 1) Length of Stay in Beds, 2) Downstream Beds Available, 3) Surgery Duration, 4) Surgical Demand, 5) Emergency Arrivals, and 6) Elective Arrivals.

Appendix E. – Improvements from decision integration on ORSP objective functions

This appendix summarizes the key improvements resulting from decision-level integration. Table E1 lists the papers and decision levels used. The columns "Base Scenario" and "Scenario Analysis" describe the default and alternative scenarios evaluated, while the objective details the assessment metrics used for comparison. Finally, the remaining two columns present the gaps obtained in each comparison and the average gap. The gap is computed by $100\% \cdot \frac{(ScenarioAnalysis - BaseScenario)}{BaseScenario}$.

Table E1. Improvement obtained by mixed decision level models.

Paper	Level[1]	Base Scenario[2]	Scenario Analysis[3]	Objective	Gaps	Average Gap
Anjomshoa et al. (2018)	S-T	Base Plan	Base Plan with 5, 10, 15, 20, 25 changes	Total income	−5,84 % | 4,92 % | 7,48 % | 9,99 % | 11,26 %	5,56 %
				Overdue patients	−3,70 % | −3,70 % | −3,70 % | −4,38 % | −3,70 %	−3,84 %
				Waiting list size	−1,20 % | −2,49 % | −3,73 % | −4,93 % | −6,96 %	−3,86 %
Oliveira et al. (2022)	S-T	Static Approach	Flexible and Rolling Horizon Approaches	Total tardiness	−2,11 % | −6,24 %	−4,18 %
				Total Waiting Time	−1,60 % | −5,04 %	−3,32 %
				Throughput	5,17 % | 12,26 %	8,72 %
Agnetis et al. (2012)	T-O	Stable Plan	Change Policy 1, 2, 3, 4, 5	Number of cases	3,23 % | 4,30 % | 4,30 % | 3,76 % | 1,61 %	3,44 %
				Number of late cases	−8,70 % | −27,54 % | −37,68 % | −56,52 % | −13,04 %	−28,70 %
				Empty time unit	−78,05 % | −97,78 % | −98,89 % | −99,11 % | −30,60 %	−80,89 %
				Waiting Time	−4,55 % | −6,06 % | −4,55 % | −13,64 % | −3,03 %	−6,36 %
Agnetis et al. (2014)	T-O	Iterative	Integrative	Total surgery score	0,07 %	
Van Huele and Vanhoucke (2015a)	T-O	Iterative	Integrative	Patients get processed	3,94 %	
				Rejection	−65,52 %	
				Overtime Cost	−12,26 %	
Aringhieri et al. (2015)	T-O	SCAP	MSS + SCAP	Patient waiting time	−0,08 %	

[1] **Levels**: Strategic-Tactical (S-T), Tactical-Operational (T-O).

[2] **Base Scenarios**: Base Plan (Initial hospital plan), Static Approach (Fixed annual plan), Stable Plan (Consistent MSS throughout the year), Iterative (Separate tactical and operational decisions), SCAP (Operational decisions based on a reference MSS).

[3] **Scenario Analysis**: Flexible Approach (Integrated yearly plan), Rolling Horizon (Yearly plan reassessed weekly), Change Policy 1 (Up to two MSS changes every 4 weeks), Change Policy 2 (One MSS change per week), Change Policy 3 (MSS remains for three months, then revised), Change Policy 4 (Weekly MSS changes without restrictions), Change Policy 5 (One MSS change per week relative to a reference MSS), Integrative (Simultaneous tactical and operational decisions), MSS + SCAP (Concurrent tactical and operational decisions).

Appendix F. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cor.2025.107063.

Data availability

Data will be made available on request.

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