Integrated Planning in Hospitals: A Review

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Abstract

Efficient planning of scarce resources in hospitals is a challenging task for which a large variety of Operations Research and Management Science approaches have been developed since the 1950s. While efficient planning of single resources such as operating rooms, beds, or specific types of staff can already lead to enormous efficiency gains, *integrated planning* of several resources has been shown to hold even greater potential, and a large number of integrated planning approaches have been presented in the literature over the past decades.

This paper provides the first literature review that focuses specifically on the Operations Research and Management Science literature related to integrated planning of different resources in hospitals. We collect the relevant literature and analyze it regarding different aspects such as uncertainty modeling and the use of real-life data. Several cross comparisons reveal interesting insights concerning, e.g., relations between the modeling and solution methods used and the practical implementation of the approaches developed. Moreover, we provide a high-level taxonomy for classifying different resource-focused integration approaches and point out gaps in the literature as well as promising directions for future research.

Keywords: Operations Research, Hospital, Healthcare, Integrated Planning, Literature Review

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1. Introduction

A well-performing healthcare system is a crucial part of a modern society and determines people's lives and livelihood [1]. The importance of a healthcare system is also reflected in the enormous spending required. For instance, an unprecedented 10.9% of the GDP of the European Union was devoted to healthcare in 2020 [2]. It is widely recognized that demand for healthcare will further increase in the future due to demographic changes such as growth in elderly population in nearly all developed countries and increased longevity [3]. For instance, the share of over 65s (over 80s) in

Germany increased from 20.6 % (5.2 %) to 22.0 % (7.1 %) between 2011 and 2021 [4]. Due to unavailability of crucial resources such as staff (particularly physicians [5] and nurses [6]), however, increased demand cannot be addressed by simply increasing healthcare spending to fund additional treatment capacities. Instead, the available scarce resources have to be used as efficiently as possible in order to ensure the continued provision of high-quality care in the healthcare sector.

Good planning for efficient resource use in healthcare is a very challenging task due to various inherent characteristics that complicate planning decisions on all hierarchical levels – from long-term or strategic planning down to operational online decision making. These characteristics include (1) the wide-spread organisational subdivision of central entities such as hospitals [7, 8], (2) conflicting objectives and lack of cooperation between involved parties such as physicians, nurses, or administrators [9], (3) unavailability of crucial information required for planning and control [10], and (4) uncertainty and high fluctuation in the daily requirements for care [11]. Consequently, advanced planning methods are necessary in order to provide high-quality decision support to decision makers and use the available resources efficiently.

Operations Research (OR) and Management Science (MS) offer a variety of scientific approaches for the efficient management and planning of limited resources that are applied with enormous success in healthcare since the 1950s [12]. Extensive overviews on OR/MS in healthcare are provided by Pierskalla and Brailer [13], Rais and Viana [3], Hulshof et al. [12], and Jha et al. [14]. Surveys focused on methods for a particular, important resource are available for operating rooms [15, 16], inpatient beds [17], intensive care units [18], physicians [11], and nurses [19–21].

An efficient planning of single resources such as operating rooms, beds, or specific types of staff can already lead to enormous efficiency gains and improved resource utilization in a healthcare system. Approaches that focus on isolated decision making in this way, however, ignore the inherent complex interactions between different resources or organizational units [12] and, therefore, often lead to suboptimal decisions on a system level. This is particularly apparent in hospitals, which collect large amounts of advanced technology and clinical specialization, but are usually subdivided into a variety of autonomously managed departments [7, 8, 22]. Consequently, a need for OR/MS models that focus on *integrated planning* of several resources has been identified [12, 23, 24]. This *vertical integration* (integration across different resources) is considered to show great potential, and an increase in publications presenting vertically integrated approaches has been observed [12, 24, 25]. It complements *horizontal integration*, which refers to integration across different hierarchical, or temporal, decision making levels, which are traditionally subdivided into strategic, tactical, and operational offline/online [9, 26].

As noted before, the need for and potential of vertically integrated planning approaches is particularly apparent in hospitals. While hospitals are a key player in healthcare systems and account for almost 40 % of healthcare spending in OECD countries [2], they are typically organized as clusters of autonomous departments, and planning is also often functionally dispersed [22]. The clinical pathways of patients, however, usually traverse multiple departments [12] where different resources are needed for providing effective treatment, which provides a strong motivation for integrated planning of these resources across departments.

Consequently, this paper provides the first literature review that focuses specifically on the OR/MS literature related to vertically integrated planning in hospitals. We collect the relevant literature and analyze it with regard to different aspects such as uncertainty modeling and the use of real-life data. Several cross comparisons reveal interesting insights concerning, e.g., relations between the modeling and solution methods used and the practical implementation of the approaches developed. Moreover, we provide a high-level taxonomy for classifying different resource-focused integration approaches and point out gaps in the literature as well as promising directions for future research.

The rest of this paper is organized as follows: Section 2 describes our literature search methodology. The set of relevant papers resulting from the search is then analyzed in Section 3 regarding the time of publication and publication outlets. Section 4 presents our taxonomy for classifying the different vertical integration approaches used in the papers according to three levels of integration. Afterwards, Section 5 analyzes which (combinations of) resources are most frequently planned in an integrated fashion. Section 6 then focuses on the modeling and solution methods (including methods for uncertainty modeling) that are used for integrated planning, while Section 7 analyzes the degree of practical implementation achieved by the developed approaches as well as the types of data that are used in the papers. Finally, Section 8 provides an outlook on integrated planning problems that link a hospital to other hospitals and other parts of a healthcare system while Section 9 summarizes and discusses our findings and points out research gaps and open areas.

2. Literature search methodology

To identify relevant literature, an extensive search was performed using the database Web of Science (`www.webofscience.com`). In order to find papers with an OR focus, the search was performed within journals that are classified as "Operations Research & Management Science" (OR&MS) according to either their Web of Science Category or their research area (or both). Moreover, several relevant journals not classified as OR&MS (e.g., Health Systems) were identified and additionally included in the search. To find papers that deal with integrated planning in hospitals, we searched for papers published until March 2023 for which at least one term from each of the three columns of Table 1 appears in the title, the abstract, or the author keywords. Here, the first column relates to hospital terms, the second to integration terms, and the third to planning terms. Whenever necessary, a wildcard ("\$" for at most one character or "$*$" for any group of characters, including no characters) has been used to represent multiple possible endings (e.g., hospital\$ will find "hospital" as well "hospitals", and integrat$*$ will find "integrate", "integrated", "integration" etc.).

The search returned a total of 1273 papers as search results, whose titles and abstracts were then examined in order to exclude papers that are irrelevant. Here, a paper was excluded if it was clear from the title and abstract that at least one of the following conditions was met: (1) The paper does not focus on hospitals, (2) no integration between multiple resources is considered, or (3) no planning or decision support using any kind of methods from Operations Research and Management Sci-

Hospital terms	Integration terms	Planning terms
hospital$	integrat∗	plan∗
clinic$	simultan∗	schedul∗
infirmary	join∗	decision∗
infirmaries	combin∗	decid∗
“medical school$”	parallel∗	allocat∗
“college$ of medicine”	multiple	assign∗
“department$”	collective∗	transport∗
surger∗	mutual∗	manag∗
surgeo∗		improv∗
		optimi∗
		minimi∗
		maximi∗
		roster∗

Table 1: Terms used in the literature search.

ence is considered. Here, following the definition used in [27], the term “resources” is broadly defined to comprise everything – from medical and non-medical staff to treatment rooms or patient appointments – that is required for the provision of healthcare (see Section 5 for a classification of different resources considered in the final set of relevant papers). Papers for which it was unclear from the title and abstract whether any of the conditions (1)–(3) are met were *not* excluded here to ensure that no relevant papers are removed from examination at this stage.

After the title and abstract screening, 318 potentially relevant papers were left. The full texts of all of these papers were then examined in detail, which resulted in an additional 135 papers that were excluded due to meeting at least one of the above conditions (1)–(3). This resulted in a final set of 183 relevant papers that were included in the review. The papers within this final set are listed in a separate bibliography titled “Search Results” at the end of the paper.

3. Temporal development and publication outlets

Based on the final set of relevant papers identified, Figure 1 shows the development of the yearly number of publications over time. While the first papers on OR/MS in healthcare and hospital contexts have been published in the 1950s [12], the earliest papers on integrated planning in hospitals found in our search stem from the early 1990s, and the yearly numbers of publications show that integrated planning did not receive significant attention in the OR/MS literature until the late 2000s. Since then, the interest in the topic has increased continuously as shown by the 3 year moving average of the number of publications.

Concerning publication outlets, most of the relevant papers (165 of 183) have been published in journals, while only a small number (18 of 183) have been published in conference proceedings. The most frequent publication outlet identified is the European Journal of Operational Research (EJOR) with a total of 31 published papers, while no other journal or conference appears more than 10 times. Interestingly, this also holds for journals with a particular focus on OR/MS in healthcare such as Health Care Management Science, Operations Research for Health Care, and Health Systems, which together only published 12 of the relevant papers.

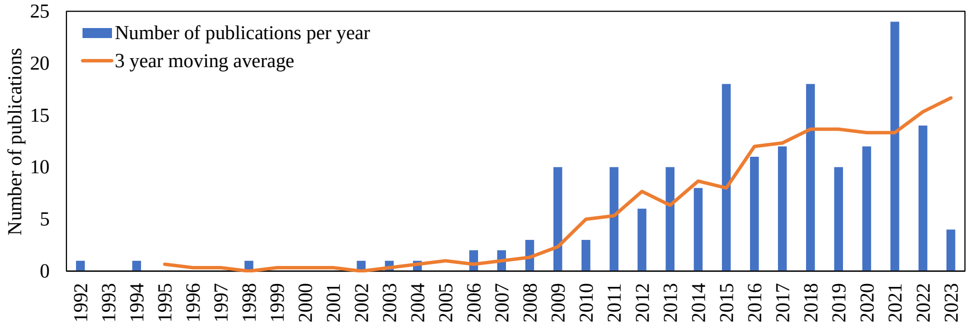

Figure 1: Number of publications over time (per year and 3 year moving average). Note that, since only papers published until March 2023 have been considered, the number of publications in 2023 is naturally lower than in the previous years. The moving average for year t considers the years $t-1$, $t-2$, and $t-3$.

4. Taxonomy of different levels of resource focused, vertical integration

In this section, we present a high-level taxonomy for classifying the different resource focused, vertical integration approaches that are used in the final set of 183 relevant papers that were identified in our literature search (see Section 2).

4.1. Definitions

In order to classify the approaches for resource focused, vertical integration used in the set of relevant papers, we categorize them according to the following three *levels of integration*, where a higher level stands for a more closely integrated planning of several resources:

Level 1 (Linkage by constraints / restrictions). Independent planning of each resource (e.g., staff) that incorporates constraints / restrictions concerning one / multiple other resources (e.g., available beds). These constraints are independent of the concrete solution of the planning problem for the other resource(s).

Level 2 (Sequential planning). The planning problems for the different resources are solved one after the other in a predefined order (e.g., first staff, then operating room, then beds) and the results of all preceding planning problems (e.g., the staff and operating room plans) are used as input for the planning problem of each resource (e.g., for bed planning). This may or may not include the possibility to return to an earlier planning problem and change this earlier problem's solution using knowledge obtained in later problems (e.g., change the obtained operating room plan since it leads to an infeasible bed planning problem one stage later) – possibly going back and forth between the problems until the overall process converges (i.e., the solutions for all planning problems satisfy certain quality criteria).

Level 3 (Completely integrated planning). All resources are planned jointly in one planning problem. Thus, decisions concerning the different resources are made simultaneously and are part of an overall solution of a single problem.

Note that level 1 is conceptually different from levels 2 and 3 in that level 1 approaches do not relate the concrete solutions of the different resource planning problems to each other. By contrast, in level 2 and 3 approaches, the concrete solutions interact either since solutions of preceding planning problems are taken as input when generating the solutions to later planning problems (level 2) or since all solutions are part of an overall solution created in a single joint planning model (level 3). While this means that approaches potentially become more complex with increasing level of integration, the tighter interaction also has the potential to yield better overall solutions.

When considering integrated planning of operating rooms and physicians, for instance, the level 1 approach for master surgery scheduling presented in [55] only takes the availability of surgeons into account via constraints, which ensure that the number of operating room time slots assigned to a given specialty in a given week does not exceed the number of slots that the specialty can cover with the available number of surgeons. Thus, the operating rooms represent the actual planned resource, while physicians (surgeons) are only incorporated via static availability constraints. By contrast, the level 2 approach in [56] first assigns blocks of surgery time to surgeons in a first stage. In the second stage, the surgical cases of each surgeon are then assigned a date and a time as consistently as possible with the first stage solution. Finally, in the third stage, the surgical cases are allocated to operating rooms consistently with the solution obtained in the second stage. Thus, the solution for the block scheduling problem of surgeons in the first stage is taken as an input for the operating room planning in the later stages. Finally, the level 3 approach for operating room scheduling presented in [57] considers operating room planning and scheduling of surgeons jointly in one model that considers both operating room decisions (e.g., the number of operating rooms to open on a day and the assignment of surgeries to operating rooms) and surgeon decisions (e.g., the start time of each surgeon). Thus, decisions about both resources are taken jointly in one planning model in this case.

Note that the distinction between the different planning levels is not completely clear in all cases and there exist papers and approaches that combine several levels – particularly when considering more than two resources. Overall, completely integrated planning (level 3) and linkage by constraints / restrictions (level 1) are most frequently applied with 107 and 76 papers, respectively, that use approaches of these kinds. Sequential planning (level 2) is far less common with only eight papers that use planning approaches classified according to this level of integration.[1]

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[1] Note that the single numbers sum up to more than the total number of 183 relevant papers since, as mentioned, some papers present one or several planning approaches with different levels of integration.

4.2. Temporal development and relation to hierarchical decision making levels

Figure 2 shows the temporal development of the 3 year moving averages of the numbers of publications using approaches of the most frequent levels 1 and 3 (level 2 has been omitted due to its low absolute frequency). Interestingly, approaches on both levels of integration started receiving significant attention simultaneously in the late 2000s. They have first been similarly common with 18 papers using level 1 approaches and 21 papers using level 3 approaches before 2012. Among the papers published since 2012, however, only 58 use level 1 approaches, while 86 use level 3 approaches. This means that completely integrated approaches that plan several resources jointly in one model have become more popular compared to approaches that plan each resource independently while only incorporating constraints or restrictions concerning other resources. This trend towards completely integrated planning approaches could be explained by both a rising interest in deeper integration between planning problems of different resources but also by increasingly powerful computers and solvers, which make completely integrated models solvable in more reasonable times than before.

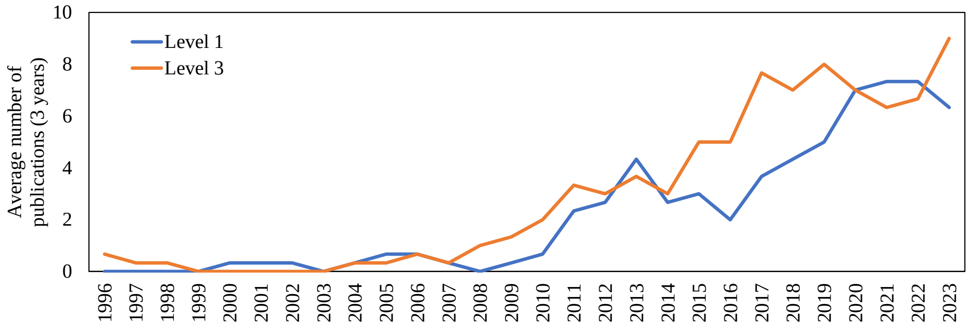

Figure 2: Number of publications as a 3 year moving average distinguished by level of integration. Level 2 is omitted due to the low number of publications.

Next, we investigate how the different levels of integration relate to the well-known hierarchical levels of strategic, tactical, operational offline, and operational online decision making [9, 26]. Table 2 shows the numbers of publications for each of the hierarchical levels in total as well as distinguished by level of integration.[2] The table shows that, for both level 1 and level 3 integration, most papers target operational problems, the vast majority of which are operational offline. Tactical integrated planning problems are studied less frequently on both levels of integration, and even fewer publications consider a strategic planning horizon – particularly among those presenting level 3 integration approaches.

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[2] Again note that the single numbers sum up to more than the total number of 183 relevant papers since some papers present several planning approaches targeting different hierarchical decision making levels and / or different levels of integration.

	Strategic	Tactical	Operational			Total
			total	*offline*	*online*	
Total	24	56	126	107	19	206
Level 1	9	21	56	47	9	86
Level 2	1	4	7	6	1	12
Level 3	19	33	66	57	9	118

Table 2: Hierarchical decision making level versus level of integration.

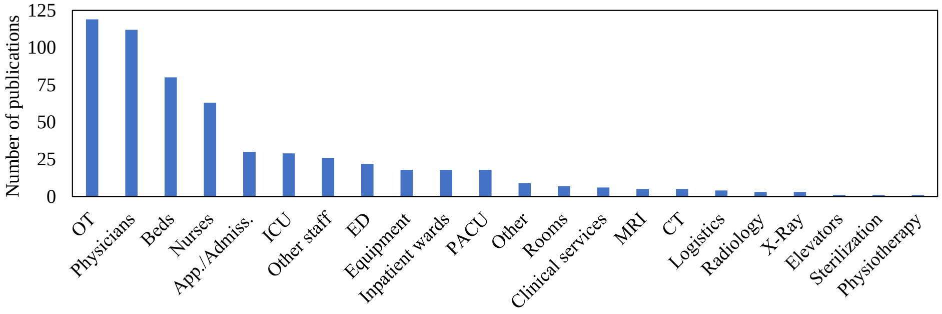

Figure 3: Absolute frequencies of considered resources overall. *App./Admiss.* and *Rooms* are used to abbreviate *patient appointments / admissions* and *examination / treatment rooms*, respectively, while *Other* summarizes all further resources that occurred too infrequently to warrant a separate listing.

5. Resources considered in integrated planning approaches

Having demonstrated the growing interest in integrated planning problems over the the last two decades, we now analyze which resources have been at the center of attention. Initially, Figure 3 shows the absolute frequencies of hospital resources / areas considered in integrated planning approaches. The figure shows that the vast majority of publications deal with the operating room / operating theater (OT)[3], medical staff (physicians and nurses), or beds. Other frequently considered resources include patient appointments / admissions, intensive care unit (ICU) and post-anesthesia care unit (PACU), the emergency department (ED), and inpatient wards. It is notable that, with the exception of other (non-medical) staff, resources without a direct connection to patients such as clinical and sterilization services, diagnostics (e.g., imaging), or logistics have only received limited attention.

For further analysis, we aggregate some less frequent resources / areas as shown on the horizontal axis in Figure 4. Here, the umbrella term *Diagnostics* summarizes computed tomography, magnetic resonance imaging, x-ray, radiology, laboratory, medical equipment, and sterilization services; and the term *Other* summarizes clinical services, logistics, elevators, and physiotherapy.

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[3] We use OT as an abbreviation for consistency reasons since OR is used as an abbreviation for Operations Research.

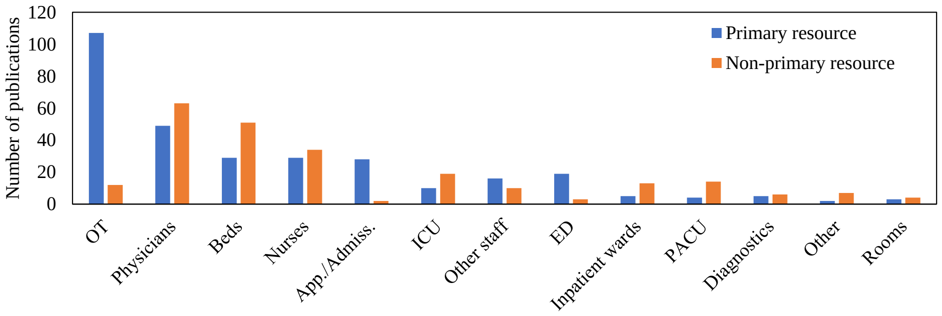


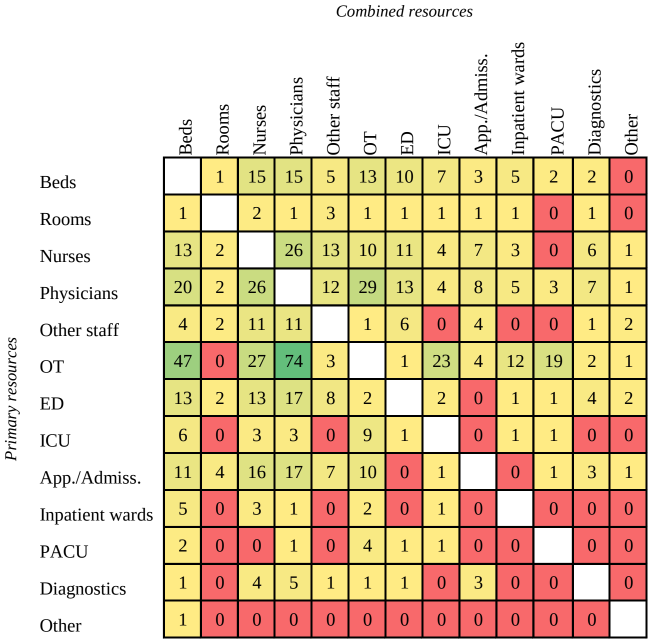
Figure 4: Absolute frequencies of considered resources distinguished by their importance (primary, non-primary). The umbrella term *Diagnostics* summarizes computed tomography, magnetic resonance imaging, x-ray, radiology, laboratory, medical equipment, and sterilization services. The term *Other* summarizes clinical services, logistics, elevators, and physiotherapy.

The analysis in Figure 4 distinguishes between primary and non-primary resources, i.e., resources / areas that are at the center of planning and ones that are supplementary. Note that, if several resources are integrated using a level 3 integration approach (see previous section), all of these resources are usually considered as primary or leading resources, but additional non-primary resources can also be included (e.g., via constraints using a level 1 integration approach). OT, patient appointments / admissions, and ED are regularly considered as primary resources, while only a small proportion of the papers containing these resources considers them as a supplement to other resources. In contrast, physicians and bed-related resources (including wards, PACU, and ICU) are more frequently considered as supplementary than primary. With nurses, diagnostics and medical equipment, and examination / treatment rooms, the results are balanced. Interestingly, while medical staff (physicians and nurses) is more often considered as a supplementary resource, other staff (including porters and technical staff) is mostly planned as a primary resource.

5.1. Considered resource combinations

We now look at specific combinations of resources that are considered and further detail the analysis regarding primary and non-primary resources. We use the same categories that have previously been introduced in Figure 4. Figure 5 displays the absolute frequencies of individual combinations of resources in a heat map linking *primary resources* in rows to *combined resources* (which can be either primary or non-primary) in columns. The number in each cell indicates the number of publications in which a link between the two corresponding resources is found. The background of each cell is color-coded ranging from dark green (highest absolute frequency) to red (absolute frequency zero). Combinations of a resource with itself are excluded for obvious reasons.

The heat map in Figure 5 reveals that *OT (primary) & physicians (combined)* and *OT (primary) & beds (combined)* are by far the most common combinations with absolute frequencies of 74 and 47, respectively. This is in line with our previous observation that the OT is mostly considered as a primary resource. Additionally, the



	Beds	Rooms	Nurses	Physicians	Other staff	OT	ED	ICU	App./Admiss.	Inpatient wards	PACU	Diagnostics	Other
Beds		1	15	15	5	13	10	7	3	5	2	2	0
Rooms	1		2	1	3	1	1	1	1	1	0	1	0
Nurses	13	2		26	13	10	11	4	7	3	0	6	1
Physicians	20	2	26		12	29	13	4	8	5	3	7	1
Other staff	4	2	11	11		1	6	0	4	0	0	1	2
OT	47	0	27	74	3		1	23	4	12	19	2	1
ED	13	2	13	17	8	2		2	0	1	1	4	2
ICU	6	0	3	3	0	9	1		0	1	1	0	0
App./Admiss.	11	4	16	17	7	10	0	1		0	1	3	1
Inpatient wards	5	0	3	1	0	2	0	1	0		0	0	0
PACU	2	0	0	1	0	4	1	1	0	0		0	0
Diagnostics	1	0	4	5	1	1	1	0	3	0	0		0
Other	1	0	0	0	0	0	0	0	0	0	0	0	

Figure 5: Heat map indicating absolute frequencies of resource / area combinations. Rows correspond to primary resources and columns to combined resources that can be either primary or non-primary. For example, the number 13 in the cell within the row *Nurses* and column *Beds* indicates the number of publications in which nurses are the primary resource and beds are considered as either primary or non-primary.

fact that physicians and beds are so frequently combined with the primary resource OT provides a possible explanation why these two resources are not the primary resource in the majority of papers considering them. A more balanced distribution of which of the two considered resources is primary can be observed, e.g., for the combination nurses & physicians, where each of the two is considered primary in 26 papers.

5.2. Resource combinations and levels of integration

We now further distinguish the considered resource combinations with regard to the level of integration. Figure 6 shows the absolute frequencies of different numbers of integrated resources differentiated by level of integration (level 2 has again been omitted due to its low absolute frequency). While two or three integrated resources are most common in both level 1 and level 3 approaches, four or more resources are also integrated in a non-negligible number of papers – especially for the more demanding level 3 integration. For the sake of a cross comparison of specific resource combinations and the considered level of integration, Figure 7 depicts two heat maps analogous to the one from Figure 5 – one for level 1 approaches and one for level 3 approaches. Recall that the number of publications for level 3 is larger than for level 1 (107 vs. 76 publications). Focusing on level 1 integration (Figure 7, left), there is

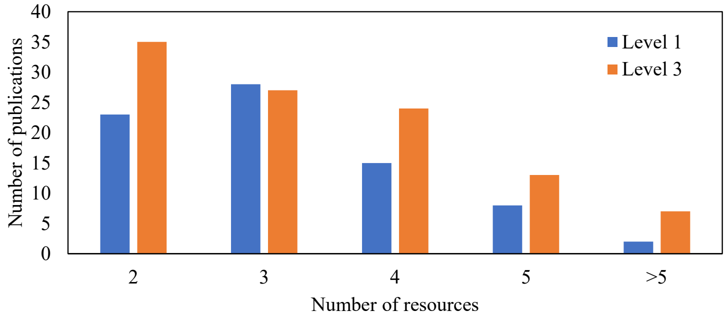
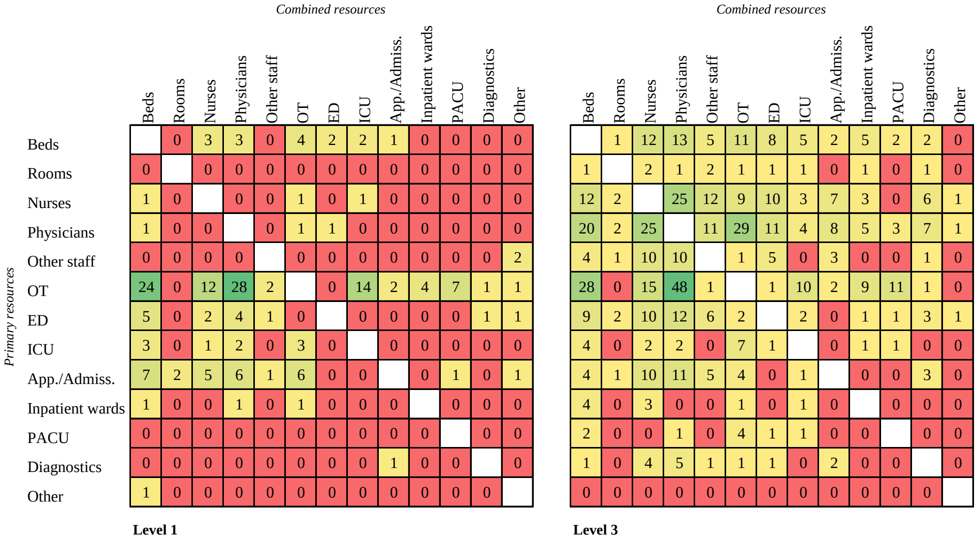


Figure 6: Absolute frequencies of different numbers of integrated resources differentiated by level of integration.



Combined resources

Primary resources	Beds	Rooms	Nurses	Physicians	Other staff	OT	ED	ICU	App./Admiss.	Inpatient wards	PACU	Diagnostics	Other
Beds		0	3	3	0	4	2	2	1	0	0	0	0
Rooms	0		0	0	0	0	0	0	0	0	0	0	0
Nurses	1	0		0	0	1	0	1	0	0	0	0	0
Physicians	1	0	0		0	1	1	0	0	0	0	0	0
Other staff	0	0	0	0		0	0	0	0	0	0	0	2
OT	24	0	12	28	2		0	14	2	4	7	1	1
ED	5	0	2	4	1	0		0	0	0	0	1	1
ICU	3	0	1	2	0	3	0		0	0	0	0	0
App./Admiss.	7	2	5	6	1	6	0	0		0	1	0	1
Inpatient wards	1	0	0	1	0	1	0	0	0		0	0	0
PACU	0	0	0	0	0	0	0	0	0	0		0	0
Diagnostics	0	0	0	0	0	0	0	0	1	0	0		0
Other	1	0	0	0	0	0	0	0	0	0	0	0	

Level 1

Combined resources

	Beds	Rooms	Nurses	Physicians	Other staff	OT	ED	ICU	App./Admiss.	Inpatient wards	PACU	Diagnostics	Other
Beds		1	12	13	5	11	8	5	2	5	2	2	0
Rooms	1		2	1	2	1	1	1	0	1	0	1	0
Nurses	12	2		25	12	9	10	3	7	3	0	6	1
Physicians	20	2	25		11	29	11	4	8	5	3	7	1
Other staff	4	1	10	10		1	5	0	3	0	0	1	0
OT	28	0	15	48	1		1	10	2	9	11	1	0
ED	9	2	10	12	6	2		2	0	1	1	3	1
ICU	4	0	2	2	0	7	1		0	1	1	0	0
App./Admiss.	4	1	10	11	5	4	0	1		0	0	3	0
Inpatient wards	4	0	3	0	0	1	0	1	0		0	0	0
PACU	2	0	0	1	0	4	1	1	0	0		0	0
Diagnostics	1	0	4	5	1	1	1	0	2	0	0		0
Other	0	0	0	0	0	0	0	0	0	0	0	0	

Level 3

Figure 7: Heat maps indicating absolute frequencies of resource / area combinations for level 1 integration (left) and level 3 integration (right).

less variety in considered resource combinations (indicated by many zeros) compared to level 3 integration. For level 1 integration, the OT is by far the most common primary resource, which is frequently combined with beds / ICU capacity or staff (nurses and physicians). In contrast, the right-hand heat map in Figure 7 indicates a much larger variety of resource combinations for level 3 integration, with staff-focused papers in particular appearing more frequently. Overall, the cross comparison of specific resource combinations and the considered level of integration reveals that the previously-observed dominance of the OT as a primary resource is mainly due to it being so frequently considered as the main resource in level 1 integration approaches, which often address OT planning with constraints concerning the availability of beds / ICU capacity and / or staff. While the OT is still often considered as as primary resource in level 3 approaches, there is also a large number of level 3 approaches that consider staff – particularly physicians – as as primary resource. In a relevant number of level 3 approaches, we can even observe that physicians or nurses are considered as a primary resource even when combined with the OT. Since other (non-medical) staff, which is ignored almost completely in level 1 approaches, is also considered much more frequently in level 3 approaches, this could indicate a shift from OT-focused integrated planning in purely constraint-related integrated planning approaches to a more staff-focused planning in approaches that perform on a completely integrated planning of several resources.

6. Modeling and solution methods

When integrating healthcare planning problems, which are often already complex individually, they potentially grow in size and, thus, might become even more difficult to solve. Therefore, choosing adequate modeling and solution methods is a highly relevant aspect. Figure 8 highlights the various approaches applied in the publications, aggregated into (a) optimization (132), (b) simulation (65), and (c) other methods, e.g., queuing theory or machine learning (52). Among optimization-focused publications, 114 of the publications use mixed-integer linear programming (MILP), while linear programming (LP) or other mathematical programming techniques (e.g., quadratic programming) are rarely used (22 in total). Among the simulation paradigms, discrete event simulation (DES) is most popular with 57 publications, while the other paradigms such as agent-based simulation (ABS), system dynamics (SD), or Monte Carlo simulation (MC) play only a minor role (11 papers in total). Lastly, other methods summarized in (c) predominantly focus on queuing and Markov models, while different concepts such as fuzzy sets or scattered use of methods such as machine learning hardly occur. Here, 18 papers using hybrid approaches indicate tailored modeling/solution concepts such as simulation-optimization or a combination of queuing/simulation and Markov/simulation. In Table 3, we visualize whether and to what extend two or more methods have been applied for solving an integrated planning problem. For optimization problems, it is common to apply only a single method when solving a problem. For simulation, however, it is more common to combine simulation (approx. 68% of the cases) with either optimization (21), other methods (14), or both (9) than to use a simulation-only approach (21). However, the use of multiple methods is typically sequential.

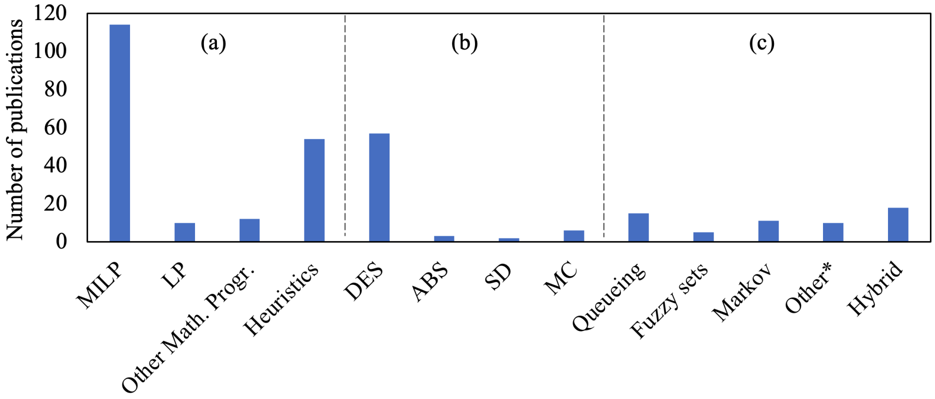


Figure 8: Absolute frequencies of methods by categories: (a) optimization approaches, (b) simulation approaches, and (c) other methods. The following abbreviations are used: *MILP* (Mixed-Integer Linear Programming), *LP* (Linear Programming), *DES* (Discrete Event Simulation), *ABS* (Agent-Based Simulation), *SD* (System Dynamics), *MC* (Monte Carlo Simulation). The term *Other** in (c) summarizes all further methods that occur too infrequently to warrant a separate listing.

	Optimization	Simulation	Other methods	All
Optimization	89			
Simulation	21	21		
Other methods	13	14	16	
All				9

Table 3: Absolute frequencies of methods applied and possible combinations. Values on the diagonal indicate that only one kind of method is used, e.g., purely simulation. “All” indicates that methods of each kind are used in a publication.

Figure 9 visualizes the evolution of the average number of publications by method categories. It highlights a steady increase of optimization-based studies since approximately 2010. Only twice we identify a decline, namely in 2013 and between 2020 and 2022, but only in small volume. Since 2022, an increase in the number of publications is observed again. Up to 2014, we observe a similar trend for simulation-focused publications, which did not increase (and even slightly decreased) towards 2021. Since 2021, however, we identify a strong increase in the volume of publications. Both increases in the number of publications (for optimization and simulation) are presumably COVID-related effects (i.e., publication backlog, or specific pandemic-focused publications). Lastly, other approaches start to appear from the late 2000s, with an increase to approximately 4 papers on average in 2018. This level is maintained to the present day.

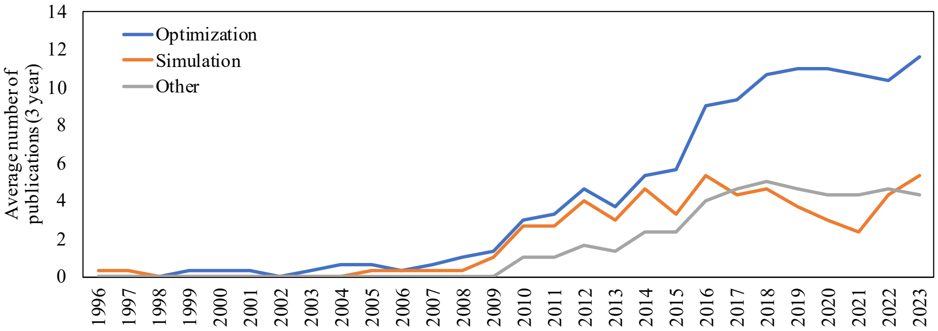


Figure 9: High-level overview of methods over time (3 year moving averages).

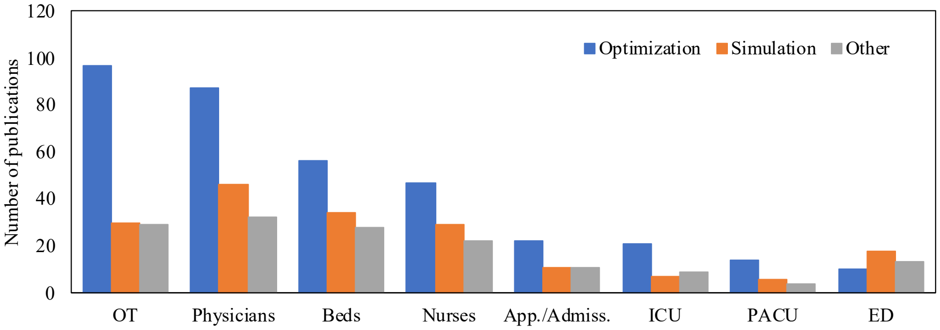


Figure 10: High-level overview of methods by most commonly found resources.

6.1. Cross comparisons with regard to modeling and solution methods

In the following, we analyze the applied modeling and solution methods depending on (1) planned resources, (2) level of integration, and (3) hierarchical decision making level. Similar to Table 3, we consider the aggregated method categories optimization, simulation, and other methods. Figure 10 shows absolute frequencies of planned resources distinguished by the three categories of methods. Usually, optimization is preferred over simulation or other approaches, which is in line with a larger share of optimization studies (see also Figure 8). For OT and physicians, the share of optimization-focused papers is disproportionately larger compared to other resources. Especially for the OT, the relative frequency of approaches using simulation or other methods is relatively small. While there are mostly fewer simulation papers, the majority of ED-related papers do use simulation. These findings also show when comparing the most common combinations of two resources (see Figure 11). Together with the previous results, we can conclude that OT-related publications predominantly use optimization, even when staff-related resources are considered as well, e.g., OT and physicians. What is interesting to note is the fact that, for purely staff-related combinations such as nurses and physicians, it is much more common to use simulation and also other approaches. In general, when no staff is involved, optimization is chosen more frequently. For the combination of ED and physicians,

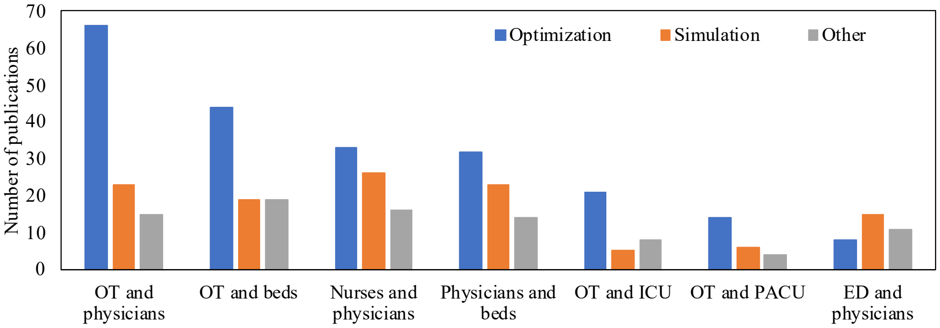


Figure 11: High-level overview of methods by most commonly found *combinations of* resources.

the share of optimization papers is the smallest among the three method categories. It is also worth noting that a combination of OT and ICU leads to the smallest share of simulation studies.

While there has been an almost steady increase in optimization papers over the last two decades (see Figure 9), simulation and other approaches do not exceed the virtual threshold of approximately 5 papers in a 3 year average. Figure 12 now investigates this further and depicts the development of method categories over time distinguished by the level of integration that the publications consider. What is interesting in this case is the fact that, in recent years, optimization-based studies see an increase in level 3 studies (blue line, dashed) while level 1 studies appear less frequently. For the two other method categories (orange and gray lines), however, we see a more similar development when comparing level 1 and level 3 approaches. For optimization, there has been a clear peak in the number of level 1 approaches between 2019 and 2022 followed by a strong decrease. Level 3 optimization approaches, however, have seen an almost steady increase, and a particularly strong increase since 2021. This could potentially be explained by computational advancements that now make possible to solve the typically more complex level 3 optimization models in more reasonable time than before.

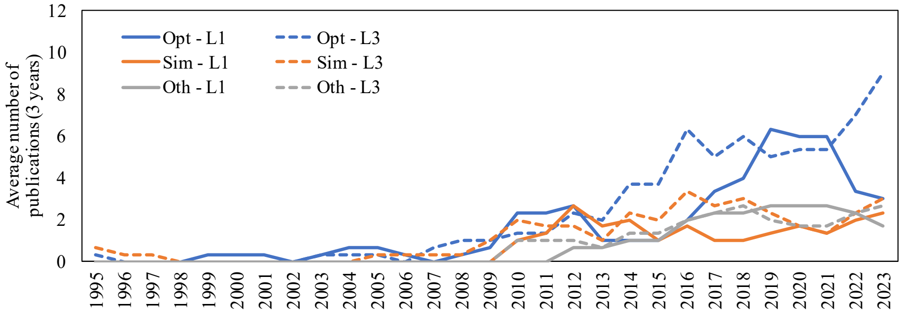


Figure 12: High-level overview of methods over time (3 year moving averages) distinguished by the level of integration.

Methods	Optimization	Simulation	Other methods
Total	132	65	52
Strategic	15	13	7
Tactical	40	23	20
Operational	94	40	29
offline/online	82/12	36/4	24/5

Table 4: Absolute frequencies of method categories used overall and distinguished by hierarchical decision making level.

Table 4 shows the numbers of publications using each method category distinguished by hierarchical decision making level. Note that papers using several methods from different categories are counted multiple times. Concerning hierarchical decision making levels, optimization approaches dominate on the tactical and operational level, while nearly equal numbers of publications use optimization and simulation approaches on the strategic level.

Among the papers that use optimization approaches, 115 focus on a singleobjective approach while only 17 consider a dedicated multiobjective approach. For level 3 problems, multiobjective approaches are slightly more common (11 of 78 at this level) compared to level 1 problems (5 of 54 publications). We did not find a clear distinction with respect to the planning horizons – across strategic, tactical, and operational, the share of single- versus multiobjective approaches is to some extent balanced (strategic: 13 versus 2, tactical: 36 versus 4, and operational: 82 versus 12). What is potentially most interesting is the fact that none of the papers that use multiobjective approaches have lead to practical applications of the developed results or methods (see Section 7 for more analyzes concerning practical implementation).

6.2. Uncertainty modeling

Most real-world planning problems in hospitals suffer from uncertainty, i.e., from incomplete information regarding some of the problem parameters or input data. Therefore, dealing with uncertainty is an important aspect of these problems. We now analyze the identified literature concerning the approaches used for dealing with uncertainty. Common ways to model uncertainty are stochastic models, robust models, and online models [28]. While the classifications *robust* and *online* apply only to optimization approaches, the classification *stochastic* can be considered for optimization, simulation, or other approaches, e.g. Markov or queuing models. In contrast to all three of these classifications, deterministic models assume all problem parameters and input data to be completely known without any uncertainty at the time the problem is solved.

Table 5 shows the overall distribution of publications differentiated by uncertainty modeling approach and level of integration. Note that a paper is counted twice if, e.g., both a robust *and* a stochastic model are presented in the corresponding publication. Values in bold font indicate the total numbers of papers (e.g., there are 56 publications in total that use deterministic planning approaches for level 3 integration) and values in parentheses indicate the numbers of papers with/without an optimization model (e.g., of the previously mentioned 56 papers that use deterministic level 3 planning approaches, 52 use an optimization model, while 4 do not).

	Deterministic	Stochastic	Robust	Online	Total
Level 1	**36** (35/1)	**43** (22/21)	**4** (4/0)	–	**76** (54/22)
Level 3	**56** (52/4)	**54** (27/27)	**6** (6/0)	–	**107** (78/29)
Overall	**93** (88/5)	**96** (48/48)	**10** (10/0)	–	**183** (132/51)

Table 5: Absolute frequencies of different uncertainty modeling approaches overall and differentiated by level of integration. The numbers in parentheses correspond to the numbers of publications using/*not* using optimization. Note that the sum of level 1 and level 3 in a column may be larger than the overall number of publications due to papers being counted twice (if two approaches are used). Similarly, the numbers for levels 1 and 3 in a column may sum up to less than the overall number in the bottom line since level 2 approaches are omitted here.

Overall, the table shows that a slight majority of papers considers uncertainty in some of the input data (104 of 183). Interestingly, the share of papers considering uncertainty is larger among papers presenting level 1 integration approaches (47 of 76) than among papers presenting level 3 approaches (58 of 107). In other words, papers presenting a completely integrated planning approach for several resources are less likely to consider uncertainty even though these approaches are more recent on average (see Section 4.2). A possible reason for this could be that completely integrated models are potentially harder to solve than models that only incorporate further resources using constraints, which could mean that considering uncertainty as well might not always be tractable in completely integrated models.

Concerning the frequencies of different uncertainty modeling approaches, it turns out that, for both level 1 and level 3 integration, the vast majority of papers that consider uncertainty use stochastic approaches (96 of 98), only a few use robust approaches (10 of 98), while online approaches are not used at all. The absence of online approaches can potentially be explained by the fact that stochastic and robust modeling approaches stem from the field of OR/MS considered here, while online optimization has its origins in computer science [28].

Another interesting observation is that almost all of the presented deterministic approaches are optimization models (88 of 93), while simulation approaches and other approaches almost always consider uncertainty in at least some of their input data. One reason for this could be that considering uncertain parameters is generally easier in simulation models than in optimization models.

While it is very common for simulation models to consider a large number of uncertain parameters simultaneously, a choice must often be made in optimization models to consider only a limited number of uncertain parameters. Therefore, we now analyze which parameters are most frequently considered as uncertain in optimization models. Since the considered (uncertain) problem parameters naturally depend on the planned (primary) resources, however, we first analyze the resources that are planned within optimization models considering uncertainty. Here, we observe that most of the papers that consider uncertainty in optimization approaches focus on the OT (41 papers), followed by physicians (34), beds (25), nurses (21), and ICU (11). Only few papers focus on the remaining resources such as other types of staff (8), inpatient wards (7), or the ED (6). Interestingly, only very few of these papers consider only two resources – the vast majority considers between three and five resources. Turning to the analysis of which parameters are considered as uncertain, we observe that, when the OT is considered as a resource, the surgery duration is by far the most frequently used uncertain parameter in optimization models. Despite OT planning being a well-studied field of research, we identified only a limited number of papers that model factors other than the surgery duration to be uncertain. Among these uncertain parameters are arrivals, i.e., authors consider the number of arriving patient as uncertain [58–62]. This may in some cases include the possibility of emergency arrivals as a separate source [60, 62–64], which are otherwise only considered implicitly, e.g. as a proportion of the non-emergency arrivals or via OT time reservation [65]. Other uncertainty aspects such as no-shows [64], patients reneging from waiting list [58] or cancellations of surgeries [58], are only considered a few times. When the OT is linked with up-/downstream resources, uncertainty in the length of stay is frequently considered. Unusual (i.e., not frequently modeled) uncertain parameters are the discharge rate of patients (from a hospital unit) [60], the demand for beds (similar to uncertain arrivals) [66–68], or nurse or surgeon availability [62, 69]. The paper by Hulshof et al. [70] is the only one to consider the care pathway of patients to be uncertain. Lastly, it is interesting to note that papers using a robust approach to solve an OT-related problem unanimously focus on the surgery duration as the uncertain parameter [61–63, 71–76]. Very few of these papers consider other parameters to be uncertain, e.g., the need for surgery [61], surgeon availability [62], emergency arrivals [62, 63], or length of stay in a downstream unit [71, 73]. Within the 14 papers in which the OT is *not* considered as a resource, we found that the arrival rate of patients (or the number of patients, including one paper modeling no-shows) [77–84], treatment durations [78, 83, 85], and bed demand [86] are commonly-used uncertain parameters. Again, in almost all cases, the uncertain parameters are patient- or demand-related, while one of these 14 publications investigates pharmacies inside hospitals and considers the delivery of medicines as uncertain [77].

7. Practical implementation and data

We also scanned our search results for information on practical implementation and the use of real data. Here, we observe two principal ways in which methods or results are used in practice. The first way is that the corresponding paper makes a suggestion for a one-time change in practice that is subsequently implemented at one or several partner hospitals. For example, Toronto's Mount Sinai Hospital eliminated its Thoracic Surgery service during budget negotiations based on an advice from Blake and Carter [87], and recommendations made by Kortbeek at al. [80] based on their research on the trade-offs between appointment scheduling constraints and access times were implemented in the Academic Medical Center in Amsterdam. The second way in which methods and results are used in practice is that the corresponding paper present a decision support tool that is then used on a regular basis to solve recurring integrated planning problems in hospitals. For example, the integrated surgery scheduling approach developed by Ozen et al. [88] was implemented as a web-based application and integrated into the existing surgical planning systems at Mayo Clinic.

Overall, only 20 of the 183 relevant papers that resulted from our search report an actual application of their work in practice in one of the above-mentioned ways. In

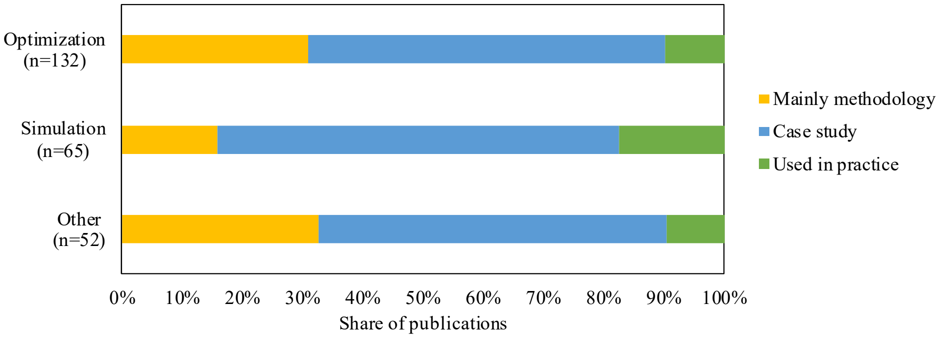


Figure 13: Degree of implementation across methodological focus areas.

contrast, 110 papers present a case study without mentioning a practical application, and 53 papers have a primarily methodological focus, i.e., they describe a new model or solution approach that is not directly connected to a case study or a practical application. Among the papers that do mention a practical application of their results, the earliest one was published already in 2002 on strategic resource allocation in acute care hospitals [87].

Analyzing the degree of practical application depending on the utilized modeling and solution methods as shown in Figure 13, we observe that the highest share of publications whose results are used in practice is found among those using simulation methods, while the share of papers that are mainly methodologically focused is by far the lowest among papers using simulations. Among both the papers using optimization methods and those using other methods, the share used in practice is much lower, while papers with a methodological focus have a much higher relative frequency. Throughout all three categories of methods, however, the vast majority of papers present case studies that have not lead to practical applications of the developed methods and results afterwards.

Concerning the use of real-world data, it is not surprising that 19 of the 20 publications reporting practical implementations use real data, while the remaining one at least uses realistic data, i.e., artificial data that has been validated as realistic through discussions with practitioners and / or literature research. Given the low overall number of 20 papers in which the authors report practical applications of their work, it is more surprising that the vast majority of the papers in our search results (121 of 183) still report on the use of real data. Together with the above observation that the number of case studies vastly exceeds the number of papers that have lead to practical applications, this suggests that obtaining real data on integrated planning problems in hospitals to use in a case study is significantly easier than actually bringing the results of a research project from this area into practice. Moreover, even the 20 papers that report practical applications of their methods or results mostly provide only brief descriptions about practical impact and / or implementation in the publications themselves in one or two paragraphs at the end of the paper. This could indicate that scientific journals and conferences that publish work on integrated planning in hospitals do not put much emphasis on the description of practical applications of the obtained results so far.

While cross comparisons of the obtained degree of practical application and the level of integration or the considered primary resources do not yield any significant insights, another noteworthy observation is that all of the publications whose results on integrated planning are used in practice report about practical applications in Europe or the Americas, while no transfers into practice are reported in the rest of the world.

8. Integration with other parts of a healthcare system

Since hospitals usually have dependencies with many other care providers and healthcare services, this section provides an outlook on existing planning approaches that link a hospital to other hospitals and other parts of a healthcare system.

From a patient's point of view, hospitals are one part of their overall care pathway. For example, emergency patients might have been taken to the emergency department of a hospital by an ambulance. Elective patients have been diagnosed and potentially treated previously by general practitioners or specialists and have then been transferred to a hospital for further treatment. During their hospital stay, they might need medication or blood bags that must be ordered and delivered, or they might need to be transferred from one hospital to another. Afterwards, patients may receive follow-up care at home or are transferred to a rehabilitation facility.

In the following, we distinguish three kinds of dependencies of hospitals with other entities in a healthcare system based on the position of these entities on a patient's care pathway:

1. *Pre-hospital dependencies:* Dependencies with care providers or healthcare services that are positioned before a hospital stay on a patient's care pathway,
2. *During-hospital dependencies:* Dependencies with other hospitals, care providers, or healthcare services (e.g., blood banks) that are relevant during a patient's hospital stay,
3. *Post-hospital dependencies:* Dependencies with care providers or healthcare services that are positioned after a hospital in a patient's care pathway.

An overview of dependencies of a hospital within a healthcare system that distinguishes between pre-, during-, and post-hospital dependencies is shown in Figure 14. For many of these dependencies, a simultaneous consideration and an integrated planning of the involved resources can be beneficial from both a patient and a system perspective and can even improve individual objectives for the involved care providers. In the following, we look more closely at three examples, one for each case, that have already been addressed in the OR/MS literature.

8.1. Pre-hospital dependencies: Ambulance diversion and offload delay

While hospitals naturally interact at least indirectly with most entities that are usually positioned before a hospital stay on a patient's care pathway (e.g., general practitioners), one of the most-studied and most direct interdependencies is

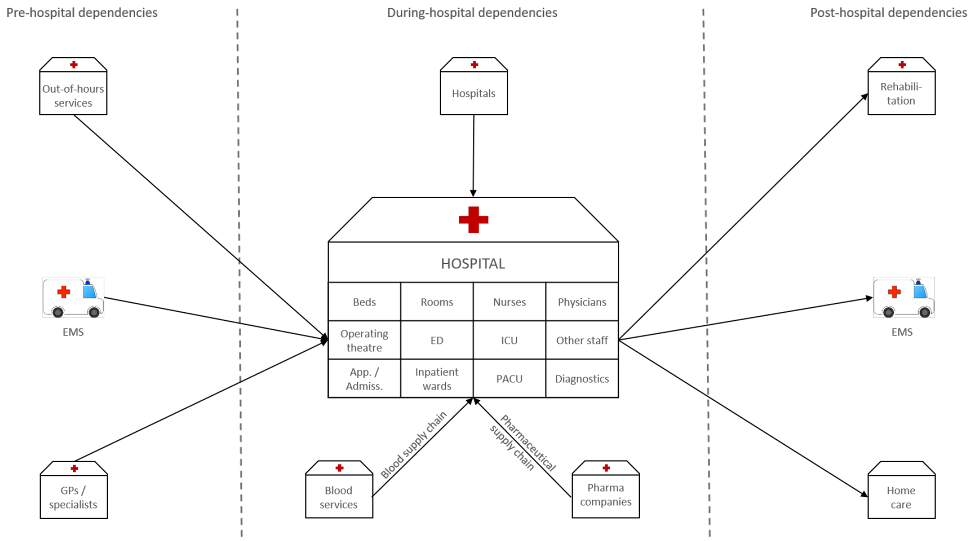


Figure 14: Overview of dependencies of a hospital within a healthcare system.

between between emergency departments (EDs) of hospitals and emergency medical services (EMS). When an ED is crowded, ambulances might need to be diverted to other hospitals, which is referred to as *ambulance diversion*. Alternatively, they might wait in front of the hospital until patients can be admitted to the ED, which leads to a so-called *(ambulance) offload delay*. As defined in Li et al.'s literature review on offload delay [29], "ambulance offload delay (AOD) occurs when care of incoming ambulance patients cannot be transferred immediately from paramedics to staff in a hospital emergency department." Optimal control policies for ambulance diversion as a countermeasure to avoid offload delay are, for example, proposed by Ramirez-Nafarrate et al. [30]. Besides others, Allon et al. [31] study the impact of hospital size and occupancy on ambulance diversion in the US, and the effects of ambulance diversion are reviewed by Pham et al. [32].

So far, the OR/MS literature mainly addresses the ambulance diversion and offload delay problems from only one side, either focusing on the EMS or the ED, even though an exchange of information between EMS and ED together with a system-wide perspective is crucial in order to enable integrated planning [33].

8.2. During-hospital dependencies: Inter-hospital collaboration

Many different kinds of dependencies of hospitals with other kinds of care providers and healthcare services are relevant during a patient's hospital stay and are therefore investigated in the OR/MS literature. Important examples include interactions with other entities in specific parts of a hospital's supply chain such as the blood supply chain [34–36] or the pharmaceutical supply chain [37].

Another important aspect that we focus on here and that relates directly to hospital resources is inter-hospital collaboration in the form of resource sharing. This means that different hospitals collaborate by sharing expensive resources such as imaging devices in order to gain efficiency. One main advantage of this type of inter-hospital collaboration is that "hospitals can avoid the purchase of expensive medical resources and patients can be treated in a timely manner in any available hospital, which will improve their quality of care." [38]. Ideally, this leads to an integrated planning of the shared resources. Since resources such as imaging devices are usually not portable, one of the most crucial aspects of this is to plan how patients should be referred between the collaborating hospitals when the shared resources are required for their treatment. This question has, for example, been studied in [38–40]. Chen and Juan [39] consider the problem of daily patient referrals for CT scans between three hospitals, while Chen et al. [40] and Chen and Lin [38] investigate referring patients between two or multiple cooperating hospitals, respectively, that share imaging services.

A related kind of hospital collaboration that also leads to patient referrals is utilization leveling among multiple hospitals with the goal of reducing disparities between the involved hospitals utilization rates. For example, Li et al. [41] study when patients should be referred from a high-utilization hospital to a low-utilization hospital and Li et al. [42] extend this investigation to a network of one high-utilization hospital and three low-utilization hospitals. Nezamoddini and Khasawneh [43] also integrate capacity allocation decisions by determining the optimal resource levels of EDs in several hospitals while considering patient transfers between them.

Overall, while the question of patient referrals between resource-sharing hospitals or hospitals with different utilization rates has already been investigated as shown above, there does not seem to be much existing work that considers other aspects of integration that could potentially be relevant in settings in which equipment such as imaging devices is shared between hospitals.

8.3. Post-hospital dependencies: Bed blocking

Hospitals also interact in various ways with care providers that treat patients after their hospital stay. The perhaps most-studied aspect of these interactions is bed blocking in hospitals, which occurs when patients in a hospital are ready to be discharged but have to remain in the hospital until a bed in a follow-up care facility (e.g., in rehabilitation center or nursing home) becomes available [44, 45]. Bed blocking can not only be harmful for patients due to the delay in advancing to the next step of their care pathway, but is also often costly since a hospital bed is more expensive to operate than, e.g., a geriatric bed [45]. The problem of bed blocking has been studied intensively in the literature (see, e.g., [46–50]) and it has been recognized that better integration and cooperation between hospitals and follow-up care facilities is necessary in order to prevent it. For instance, Mur-Veeman and Govers [47] state in their work on buffer management in Dutch hospitals to solve bed blocking that "although stakeholders recognize that cooperation is imperative, they often fail to take the actions necessary to realize cooperation." Motivated by the improved integration that is needed in order to solve the bed blocking problem, Chemweno et al. [48] model the complete care pathway for stroke patients to analyze the effects of different intervention strategies aimed at minimizing patient waiting time delays for available bed resources. Using simulation, they show that maximizing the bed resource utility leads to a decrease in patient waiting times. Rashwan et al. [49]

use system dynamics for obtaining a holistic and strategic national level capacity-planning model to address the problem of acute bed blocking in the Irish healthcare system, while Wood and Murch [51] address the general problem of blocking after any service along the patient pathway using a continuous-time Markov chain.

In summary, bed blocking has already received considerable attention in the literature. In addition, the necessity for integrated models that address the problem by looking at all involved entities along the relevant care pathways has already been recognized. Nevertheless, such integrated models still seem to be scarce.

9. Summary, discussion, and conclusion

This section concludes our analysis and identifies overarching trends and open research areas. In line with operating theaters being the most-studied area of the hospital in the OR/MS literature in general [15, 16, 25], our findings show that the OT is the resource that is most frequently combined with other resources in integrated planning approaches overall. Moreover, the OT is also the resource that is most frequently considered as a primary resource within integrated planning approaches. The second most common resource – both overall and as a primary resource – are physicians. When combining physicians and nurses under the umbrella term *medical staff*, however, the temporal development illustrated in Figure 15 shows an interesting trend. The different lines visualize the 3 year moving averages of the yearly numbers of publications that do / do not consider the OT or medical staff as one of the integrated resources. Despite the large number of OT-focused publications in the OR/MS domain overall, Figure 15 suggests that, since about 2010, the number of publications considering medical staff within integrated planning approaches constantly exceeds the number of publications considering the OT. The OT, however, is still the most frequently appearing primary resource even when counting physicians and nurses jointly. This suggests that the OT is still the most common center of attention also in integrated planning approaches, but medical staff has been considered more frequently as part of integrated planning approaches overall for more than a decade. This is also supported by the observation that the number of papers that do *not* include medical staff is lower compared to the number of papers that do *not* include the OT – both in total and relative to the number of papers that *do* include the respective resource. A possible explanation could stem from increasing shortages of medical staff, which might motivate to at least include staff as a supplementary resource in integrated planning problems.

When considering the number of publications that include neither the OT nor medical staff, it can be observed that the average number of such publications has stayed extremely low overall, even though the average number of publications per year has increased tremendously within the last 15 years (see Figure 2 in Section 4.2). From this we conclude that the increasing interest in integrated planning problems in hospitals observed in the OR/MS literature is so far mainly focused on planning problems linked to resources that are necessary to perform patient-related tasks (surgery, caring on a ward, etc.). In contrast, planning problems that are (further) away from the patient are still studied much less.

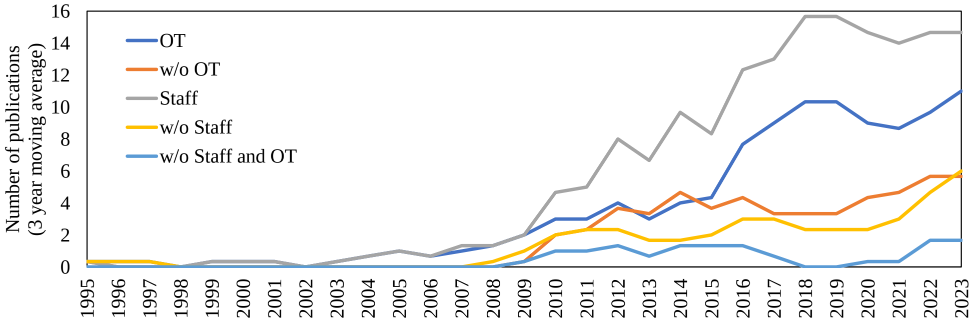


Figure 15: 3 year moving averages of the numbers of publications that do / do not consider OT or medical staff.

With regard to uncertainty modeling, we found that approximately half of the publications on integrated planning we identified consider uncertainty in one or several input parameters. However, the consideration of uncertainty seems to be more common in approaches that only integrate several resources via constraints compared to completely integrated planning approaches – even though the latter are more recent on average. This may change in the future, though, when the joint consideration of integrated planning and uncertainty becomes more and more tractable due to advances in solution methods and computing power. Regarding specific uncertain parameters, durations of activities are most frequently considered to be uncertain (e.g., surgery durations or the length of stay on a ward). Even among the relatively large number of papers considering integrated planning problems that combine the OT with either medical staff or beds, only very few papers consider parameters other than durations to be uncertain (e.g., no-show rates, the availability of staff, or the availability of beds) – even though unavailability of (medical) staff, for example, has already been identified as a highly relevant aspect within the (healthcare) personnel scheduling literature [11, 52, 53]. Since medical staff is usually required for the vast majority of activities along a patient's pathway within a hospital and is often hard to replace both in the short and long term, uncertain staff availability seems to be an especially relevant aspect that should be considered more in future research.

Regarding the practical implementation of the research work on integrated planning problems in hospitals, we summarize that there is only little evidence that case studies conducted as part of such work lead to implementation of the obtained findings in daily practice. This is in line with the results of previous literature reviews that – while not focusing specifically on integrated planning – also found little evidence for successful implementation of research output [11, 25, 54]. If research on integrated planning does influence decision making within a hospital, we found that simulation studies are more likely to initiate such changes. A promising avenue towards implementation of findings and initiation of changes requires OR/MS to develop strong links not only to all involved personnel and hospital decision makers, but also to informatics [11]. The latter is required to embed the developed approaches into hospital information systems in order to make them accessible for planners and decision makers as part of their daily practice.

9.1. Research gaps and open areas

Despite the large number of publications that meet our inclusion criteria, the focus in terms of hospital areas and resources is still rather narrow. It becomes clear that there is a shortage of non-OT-focused publications, which might be due to the *popularity* (or importance) of the OT itself or a lack of effort to explore other areas. A stronger focus on staff could be particularly promising here since staff shortages in hospitals are already visible and are expected to intensify in the future as population ageing increases demand for care relative to the size of the healthcare workforce. While staff is already the most considered supplementary resource overall in integrated planning problems, we therefore expect also the center of attention to shift from the still mostly OT-focused planning observed so far to workforce-focused planning as a driver of future research. Moreover, supply services such as sterilization or pharmacy have not yet been included in integrated planning approaches. We therefore believe that increasingly considering activities that do not immediately include patients (such as hospital pharmacies, sterilization services, or inventory of medical and non-medical supplies) may represent a promising avenue for future research.

With regards to uncertainty modeling, the planning parameters that are considered as uncertain are so far mainly limited to durations. Notably, other very important issues such as no-show rates or availability of resources (staff, beds, etc.) are only rarely considered despite the substantial knock-on effects they can lead to in an integrated planning setting. No-shows of patients or other unexpected changes in patient demand might be particularly relevant here since the patient is usually the linking element between various steps along the care pathway [24], so uncertain patient availability and demand will likely affect several parts of an integrated planning problem simultaneously. Staff unavailability, on the other hand, could become more and more important in the future due to the above-mentioned changes resulting from the graying population. Overall, we expect the uncertainty of parameters such as the number of available nurses, qualification levels of staff, the care chain (e.g., what resources are needed to treat a patient and are they actually available), and, finally, the flow of patients itself to be studied more in future research on integrated planning. Doing so could be especially valuable since the effects of these and other uncertain parameters a well as knock-on effects caused by patient or resource unavailability can be much better understood with an integrated perspective (e.g., uncertain staff availability in the PACU can influence the number and types of surgeries that can be performed on a day and, therefore, also the number of beds required on the ICU or regular wards in the following days). This seems particularly true for staff-related effects since staff typically works in various places of a hospital (e.g., in the OT, the ICU, on wards, or in offices) and is sometimes required to switch roles / positions during the day or week, which makes integrated planning seem inevitable in order to grasp the full consequences of uncertain staff availability and, as a result, ensure consistent availability of staff with the right expertise at the right place.

We conclude this discussion and our analyses of publications on integrated planning problems in hospitals with the following *take-home messages:*

1. *The further planning problems move away from patients, the fewer integrated studies exist.* While patients are the main connecting element between resources

and areas of a hospital to be integrated (and their pathways are often uncertain, too), there is still a lack of integrated studies that consider resources and activities that do not immediately include patients (e.g., sterilization, medical and non-medical supplies).

2. *Medical staff usually work in different places, which makes it even more important to consider integrated planning approaches.* Instead of following the patient through the hospital, movements of and requests for staff will be an interesting topic to follow.
3. *Knock-on effects (e.g., impacts of OT utilization on ward utilization) can only be fully understood if the system of interest is modeled in an integrated way.* This, in turn, suggests that simulation studies (either stand-alone [89, 90] or in connection with other planning approaches [91, 92]) might receive even more interest in the future.
4. *Successful implementation of integrated planning approaches requires the involvement of all relevant stakeholders.* Despite the substantial share of papers that test their approaches in a case study, evidence of practical impact or successful implementation is still limited. This could be at least partly due to the increased amount of stakeholder involvement that might be required to implement an integrated approach in practice. While links to the involved personnel and decision makers are important for the successful implementation of any planning approach in a hospital, they seem particularly important for implementing integrated planning approaches that often involve multiple departments or decision making units of a hospital. According to our analysis of integrated planning approaches, it seems that simulation models seem to receive more buy-in from stakeholders so far compared to other approaches such as optimization models.

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