Summary Compilation: Advanced Computational Approaches for Medical Resource Scheduling

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I, Oleksii Dovhaniuk, confirm that the work presented in this essay is my own. Where information has been derived from other sources, I confirm that this has been indicated in the work.

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Contents

Chapter 1

Compilation

1.1 SR01US23

1.1.1 Meta

Title: AI for patient scheduling in the real-world health care setting: A metanarrative review

Rank	Grasp	Type	Outcome	Domain	COV19	CoI	DB	Prooved
5	90%	A	P	B	Yes	No	??	No

Table 1.1: Reference's metadata

1.1.2 Summary

Dacre Knight et al. [1] conducted a metanarrative literature review for Artificial Intelligence and Machine Learning technologies implemented in healthcare. The researchers define three types of studies: pre-pilot, pilot and implemented. Major databases were searched on August 14, 2020, and only the publications of the third type were selected for deeper review. The review paper highlights the advantages and obstacles of using AI technologies in healthcare. The authors consider their work's limitations and outline future research directions.

1.1.3 Notes

- Studies split into three stages: pre-pilot, pilot, implementation;
- 11 implemented works;
- general statements, low-on-insights reviw;
- 2 reviewers + consultant investigator

1.1.4 Reading

Title page: Metadata of the paper: title, authors, PII, DOI, Reference, Jornal: Health Policy and Technology, citation, remark about possible editing during the publication process

Page 1: Authors affiliation details + Reprints

Page 2: More metadata: keywords, conflict of interest, no funding, no ethical approval required, technical content details, short title: AI for Patient Scheduling, highlights: 4 highlights about possibility and high potential of an AI in the healthcare scheduling.

Page 3: Objectives: The artificial intelligence and machine learning approaches are uncharted teritory in the optimal scheduling.

Methods: The authors use systematic review of publications starting from August 2020. The reviews of literature were conducted by two independent specialists per each article.

Results: Areas of AI application are: double-booking, missed appointment risk, wait time, disease-type matching performance, scheduling efficiency, examination length prediction, and surgical operation time.

Conclusions: Prooved the AI compentence and found new ravenues for development

Page 4: Public Interest Summary: AI valuable asset which is shown in this literature review update.

Page 5: The same hihglights that before

Page 6: Abbreviations - AI, ML, Operation Room

Page 7: Here is the introduction of the paper where the financial aspects are alligned with the healthcare management efficiency and how the AI/ ML technologies can enhance this efficiency.

Page 8: Wrap up of the introduction where the authors hihglight versatility of the AI approaches used for reducing healthcare costs and optimising the workflow of the medical services. Also it is mentioned that not only benefits of the AI is in focus of this research but also obsticalse which may arise by utilising AI technology.

Begining Methods section: metanarrative following RAMESES guidances (6)

Page 9: The authors separates three types of studies based on the stage of the study (pilot study, solution testing, and actual application). In the review the only 3rd type publications are accepted into the review. Also in the literature search section, the used databases of materials are listed together with teir years of work.

Page 10: Date of the search is August 14, 2020 and the full search is available in the Supplenental Material.

Data Screening and Extraction $\approx$ Data Analysis (start): two reviewers study selection $->$ 3rd seniour investigator to resolve the conflicts $->$ data extratcion (approach, stakeholder impact). descriptive statistics, no quantitative pooling (no metaanalysis)

Page 11: 3,415 sudies in search $->$ 261 full review $->$ 11 reald world studies. 8 countries (US. China, Switzerland, Singapore, India, Iran, Austria, and Finland). Due to difference of application studies have different requirements for datasets.

Page 12: The authors used Risk of Bias in Non-randomized Studies and the Cochrane risk-of-bias tools. Also the variouse scheduling strategies were highlighted here.

Page 13: There are mostly objectives are regarding patients appointmens and some also include cancellations/ no-show risk, resource allocation,daily demand, and physician-to-patient matching. Next there is multiple results from the reviewed studies.

Page 14: More specific cases with improvements.

Page 15: Healthcare costs in USA increased by 4% from 1980 requiring more efficient approaches of hospital management, and AI/ ML technology can provide this eddiciency.

Page 16: Regression models and Markov algorithm predict no-show appointments. Patient scheduling is a multi-objective task. Nevertheless, the interest in AI is growing. (+lack of healthcare records +bias, +uncertainties)

Page 17: There are great benefits from AI in healthcare, including help in time of the COVID19 pandemic. The authors predict that AI will occupy valuable place in healthcare in the future, but for now it is important to analyse its capabilities.

Page 18: The contributors acknowledge the cons of the research, poining out small number of selected publications with real world implementations that chosen studies are not resent. Inpatients in 1 of 11 publications. AI requires quality control.

Page 19: Evaluating the ML model biases and traking progress of the technology. Conclusion: AI requires more enhancments for the actual application, review is presented, general future investigations.

1.2 SR02US22

1.2.1 Meta

Title: Current Trends in Operating Room Scheduling 2015 to 2020: a Literature Review

Rank	Grasp	Type	Outcome	Domain	COV19	CoI	DB	Prooved
5	95%	A	P	S	No	No	Has	Yes

Table 1.2: Reference's metadata

1.2.2 Summary

Sean Harris and David Claudio [2] conducted literature on current operating room scheduling trends from 2015 to 2020. This literature review updates knowledge about new studies continuing the three previous reviews. The authors also introduced new categories and metrics for structuring and analysing the findings. The categories were evaluated individually by complexity criteria, and at the end, the collective average complexity of the research works was presented. The research focuses mainly on the Operating Room Scheduling problem and less on the proposed solutions. Sean Harris and David Claudio underline the most promising future scheduler development directions. The emphasis is placed on the geographic location for the generalisation research and on the need for more practical implementations of the scheduling models.

1.2.3 Notes

- Cascade of literature reviews from 2000 to 2020;
- The geographical location by hospital or the first affiliation;
- Models generalisation from one country to another (urban to rural);
- Leeftink and Hans (153) dataset;
- Systematic texting and validation (32, 19, 230)
- Look into the next studies: 1, 8, 12, 231, 262;

- (thoughts) statistics by researchers in the fiel;

- (thoughts) geographical locations by countries and/ or cities;

1.2.4 Reading

Page 1: The abstract presents the papers as literature review based on the previous review studies in the field of operating room (OR) scheduling up to 2014. The current paper reviews 246 from 2015 to 2020 and underlines the next tengencies: the number of publications has grown in comparison with brevious years, the development continues across all categories, and there is still unsufficient number of practical implementations of the schedulers. OT is the most valuable financial asset in hospitals, and it is possible to solve the OT scheduling problem from multiple approaches.

Page 2: There is multiple benefits from conducting a literature review: organise available materials, points towart uncharted teritories, and provides common guidance for newcommers. The current literature review is build upon three previous reviews by followinf classification, but there are some works which does not follow the framed classifications.

Page 3: There are further extentions of the classification system: +location, +OR research frequency, two new subcategories in waiting time constraint, +planning horison, +scheduling policy

Table 1 Recent Literature Review Article Coverage

Review	Years Covered	# Articles Reviewed	# Articles from 2015 to 2020
Cardoen et al. [1]	2000–2009	247	–
Demeulemeester et al. [4]	2000–2010	136	–
Samudra et al. [5]	2004–2014	216	–
Zhu et al. [8]	1950–2018	315*	52
Rahimi and Gandomi [9]	2000–2019	150**	70
This review	**2015–2020**	**246**	**246**

*Not every article is classified into each of the categories; select articles are classified and used to illustrate trends; **Scientometric review focusing on modeling and optimization techniques

Figure 1.1: Previous literature reviews from [2].

Page 4: There is replicated search strategy from the previous literature review considering only English and two major databases Web of Science and PubMed.

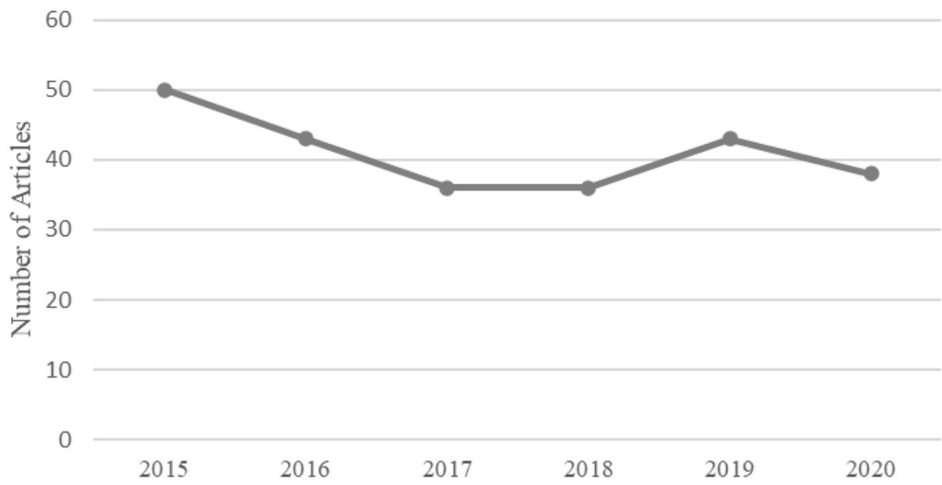


Figure 1.2: Number of articles per year [2].

Page 5: Sean Harris and David Claudio introduces complexity score for every category. Patients classification of elective and non-elective, inpatients and outpatients. If models do not use in-/outpatients classification then it is classified as general elective case. Non-elective cases can be categorised as emergent (up to 1 hour), urgent (up to 1 day), or general. 241 of 246 papers consider elective cases alone. From 2015 to 2020 the number of papers with clear separation of outpatients and inpatients decreased. Non-elective patient is a challenge for scheduling.

Page 6: There are two solutions to emergent cases: just go ahead with emergent-first; brack-in method (231). Proper schedulers evaluation is not possible due to abcense of general scheduling policy. Dedicated, shared, and hybrid OR policies are considered for non-elective cases.

Page 7: Most researchers assume that there is dedicated emergent OR. The patient's complexity scores 1 is there is elective and non-elective cases and 0 otherwise. The OR policies is still a debatable topic.

Page 8: There are divarse objectives for each of the partisipance in healthcare services: patients, stakeholders, managers, and medical personnel. Two new terms: waiting time-number of days and waiting time-within day. Financial objectives are usually competing (cancellation $<->$ overtime). Overtime not always mean overutilisation. And oferal performance values have been improved from 2015 to 2020.

Page 9: Some constraint measures are more likely to be selected with one another than others which is visulised in tables. Complexity scrore for two objectives is 0.5 and for more than two objectives - 1. There are positive trends in direction of staff sutisfaction.

Page 10: The authors state that the number of objective measurment will increase in future studies. The next three decision levels are usually considered: Case-mix planning (strategic = long), master Surgery planning (MSP = MSS = tactical = medium = 1 week), Patient scheduling (operational = short). In addition, there are three scheduling policies: block (allocation scheduling = defining start time), open (FIFO = FCFS), and modified block. The alternative way of analysing the decision aspect of the scheduling is by specialty, surgeon, and patient. The most popular is still patient-level panning.

Page 11: There are papers which considere multiple levels of decision-making at once (12, 262). Some exotic works propose solutions for OR scheduling problem and vehicle routine problem. The various planning horisons are picked for scheduling includion varying horisons.

Page 12: The planning horizon is not always assigned explisitaly. Some researchers work on dynamic scheduling but many more on rescheduling strategies which allows have idea of required capacity on weeks ahead and then more concreat scheduling in one/ two days prior to the surgery day.

Page 13: Additinonal diration is online scheduling (on-the-fly desicon-making). There is developed terminology by (1) which is good to follow.

Page 14: Upstream/ Downstream Units introduce new level of complexity to the scheduling model: hardship to generalise the research and increase scheduling time, but rewards with more applicability of the solution. From 2000 to 2014 around 50% of papers studies include at least one of the units. Most researchers select downstream unit over upstream. Medical equipment as well as sterilization processing department became popular objectives of the scheduling problem.

Page 15: The ICU models are unpredictable, thus use stochastic approaches. Incorporating turnover time is a usual practice. The authros sugest increase in investigation uncommon upstream and downstream units.

Page 16: In general, from 50% to 60% of studies incorporate uncertainties. The most common is operation duration with is good trend that should remain. Sean Harris and David Claudio also suggest to improve research in the area of rescheduling. The solution methods are ordered by frequency: mathematical models, simulation approaches, methaheuristics (60%-30% 23%).

Page 16: The research methods are not easaly classified. The heuristics reduce scheduling time in cost of 0 to 10% of optimality gap.

Page 17: In the gap between 2015 and 2020 the papers with simulation optimisation solutions begone to appear. MIP $->$ goal programming. Simulation optimisation, hybrit simulation, heuristics, and goal programming are promissing and suggested scheduling approaches.

Page 18: Future reviews should adress the scheduling methods classifications. Healthcare requires practical validation of the scheduler work. The use of real data increased to 7% which showcases the increase and availability of healthcare records and enphacise the vast room for imptovement.

Page 19: The number of implemented models from 2015 to 2020 is reduced. The level of details in research workflow is increased and the investigators benefit from interviews with medical personnel.

Page 20: Systematic texting and validation (32, 19, 230).

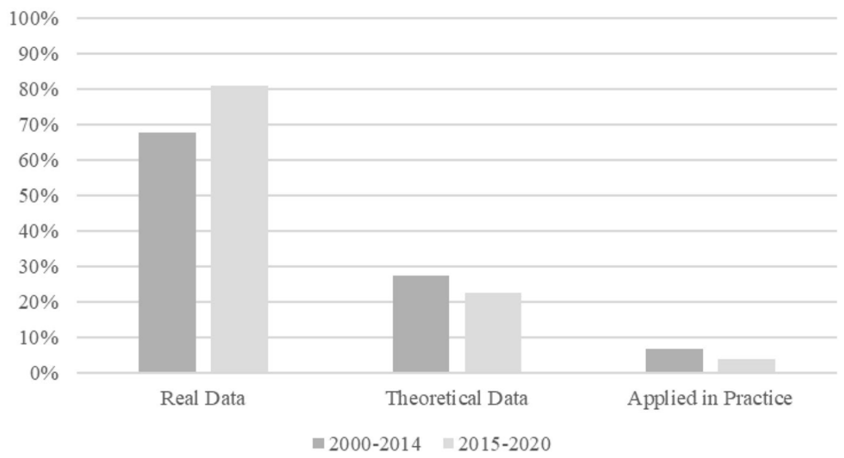


Figure 1.3: Testing and application from [2].

Page 21: Future is in generalisable findings. Location critaria is taken into account for studies with real data (Leeftink and Hans (153) does not count). USA and China are the most common origins of the OR scheduling research. Most of US is in Mayo Clinic or the Northeastern and Midwestern part of the country. In Europe the lieading position is in Italy.

Page 22: Using location cretatio opens new perspective in the literature review analysis.

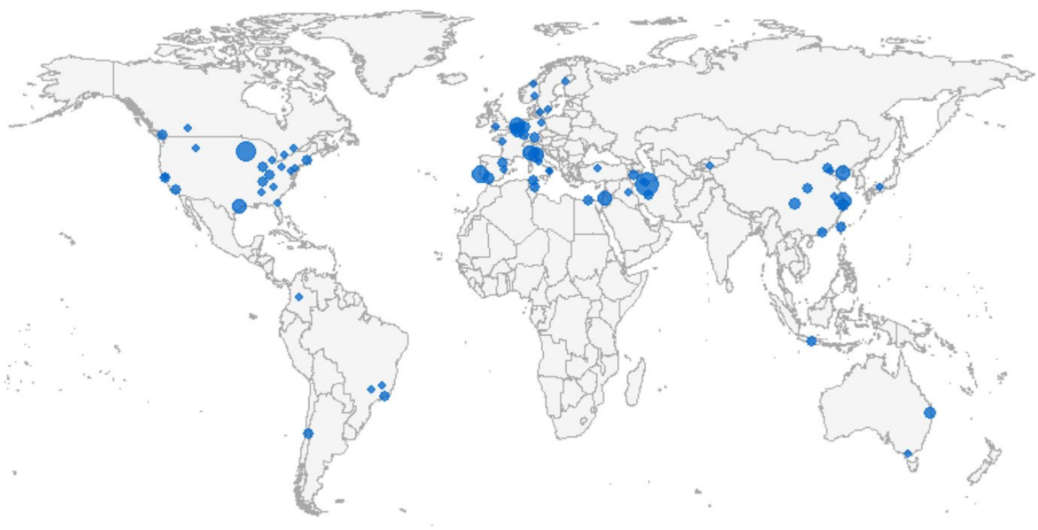


Figure 1.4: Geographic Map of Article Locations and Frequency from [2].

	Patient Waiting Time	Overtime	OR Utilization	Financial	Throughput	Makespan	Deferral
USA	0.91	1.39	0.46	**1.79**	0.73	0.70	0.49
China	0.76	1.05	0.75	**1.91**	0.19	1.37	0.32
Italy	1.52	0.57	2.09	0.55	**3.43**	0.00	0.63
Iran	1.09	1.63	0.64	0.20	0.27	1.30	**1.80**
Belgium	1.09	0.41	0.00	0.59	**1.63**	0.98	0.00
Germany	0.53	2.11	1.51	1.80	0.00	0.00	**5.72**
Netherlands	1.59	2.11	2.26	0.90	**3.35**	0.00	1.91
Spain	3.19	0.00	**3.77**	0.00	2.23	0.00	0.00
Portugal	1.06	0.00	2.26	0.00	**5.59**	0.00	0.00

Figure 1.5: Ratio of Actual/Expected Occurrence of PM by Country from [2].

Conclusions: Review on 246 studies from 2015 to 2020 was conducted. Patient type is consistant and future works are in direction of non-elective cases (centralised vs. deventralised). The tendency of multiple performance measures should continue. All decision delineations (dynamic scheduling, rescheduling and online scheduling) are continuing to be desirable areas of research. The not traditional upstream capacities could be considered for future research. Incorporating more uncertainty in OR schedulers. Research methodology lies in development of heuristics and the suggestion areas are simulation-optimisation and goal programming. More research is needed in testing and application. Innovative diraction is to consider generalisation from one geographic location to another. For the papers in the research the complexity score increases closer to 2020. The collective work shows its benefits, but the field remains scarce meaning the challeges are not easy to concore.

1.3 SP01GB23

1.3.1 Meta

Title: Machine learning models to predict surgical case duration compared to current industry standards: scoping review

Rank	Grasp	Type	Output	Domain	COV19	CoI	DB	PR	Fnd
5	94%	A	P	A	Yes	No	Yes	Yes	No

Table 1.3: Reference's metadata

1.3.2 Summary

Christopher Spence et al. [3] published a narrative literature review of machine learning models for predicting surgery durations and challenged the standardised methods in the industry with machine learning algorithm efficiency. The authors searched studies on the open source databases till July 28, 2023. From 2593 publications, only 14 were accepted by the authors for in-depth analysis. The current work clearly states the paper selection process with a graphical flow visualisation. The analysis of the ML studies includes comparing the dataset size, data management, hospital implementation, model efficiency, model complexity and some fundamental construction differences in ML models. In conclusion, the authors highlighted the superiority of the ML models over standardised approaches and, at the same time, the need for more concrete ways of implementing and generalising the ML solutions in hospitals and the existing challenges to the researchers in the field of surgery duration prediction.

1.3.3 Notes

- Libraries: PubMed, Embase, MEDLINE, ClinicalTrials.gov, and the Cochrane Central Register of Controlled Trials (CENTRAL).;
- Frameworks: PRISMA, Arksey and O'Malley;
- Check out national audit office NAO for open data;
- What is gray literature search;

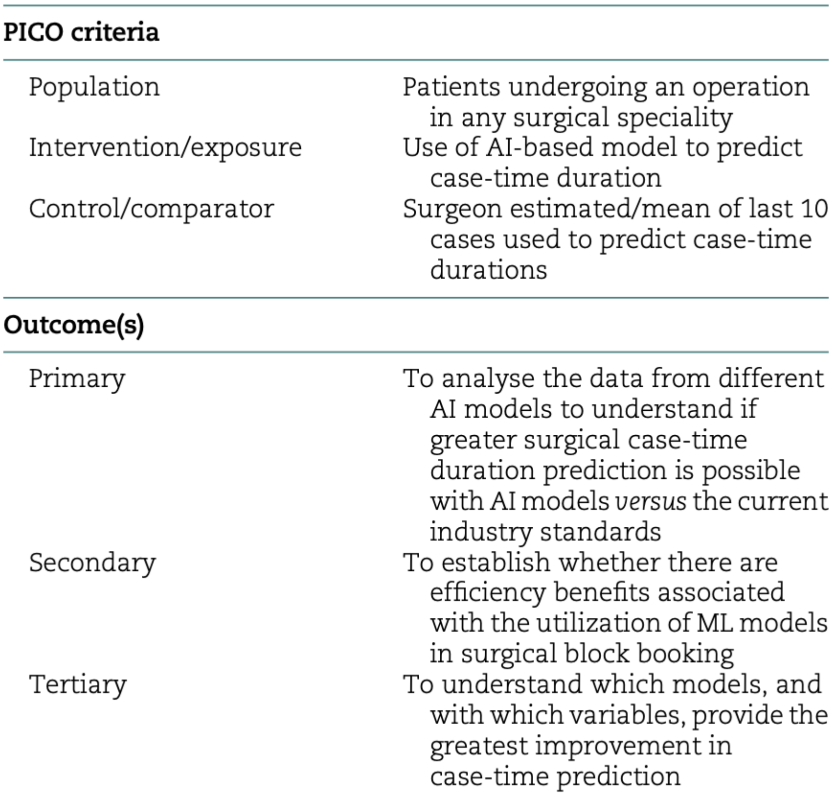
- Medical Subject Heading (MeSH);
- Oxford Centre of Evidence-Based Medicine (OCEBM);
- Sources of data: 11, 16, 18-25, 39-42;
- National database: 19, 20, 40;
- Superior study in spectrum of sample size and explonation - 24;
- Data source EHR;
- What is retrospective observational study?
- What is randomized control trial?
- Contains details comparison table;
- TRIPOD-AI (59)?
- Supplementary materials;

1.3.4 Reading

Abstract: The 2019 pandemic brings challenges to the scene of healthcare management. The novel AI approaches have been implemented in more rate. There is a question, whether the artificial intalligance approaches can substitute the existing healthcare standarts. The literature until July 2023 was selected and analysed.13 of 14 studies (2593 articles) demonstrate that machine learning is better than existing standardised approaches. NN is superiar to any other machine learning algorithm. The AI niche is surgery duration prediction, for more areas of application the further research is required.

Objectives: Compare the novel machine learning approaches for predicting surgical case duration to present industry standards.

Page 1: The consecuances of COVID-19 almost doubled the number of patients in waiting lists requiring surgery in 2023 compared to 2020. The national audit office (NAO) estimates plus four and a half million of cases by March 2025. There are mechanism to reduce waisted time. The empirical estimation of surgery duration by surgeons should be changed to more advanced approach to improve the operating theatre efficiency. There is no generalised solution. Here the authors introduce AI, ML, and DL.



PICO criteria	
Population	Patients undergoing an operation in any surgical speciality
Intervention/exposure	Use of AI-based model to predict case-time duration
Control/comparator	Surgeon estimated/mean of last 10 cases used to predict case-time durations
Outcome(s)	
Primary	To analyse the data from different AI models to understand if greater surgical case-time duration prediction is possible with AI models *versus* the current industry standards
Secondary	To establish whether there are efficiency benefits associated with the utilization of ML models in surgical block booking
Tertiary	To understand which models, and with which variables, provide the greatest improvement in case-time prediction

Figure 1.6: PICO framework from [3].

Page 2: DL has more then 4 layers. DL is promising diraction for estimating the surgery duration, and it already has success in other healthcare scenarios. ML require accurate training dataset to produce efficient results. PRISMA protocole was developed for the literature scoping (can b accessed on request). Formulate research question: are AI approaches better? The search on each database to 28 July 2023. The titles and anstractes screened separatly and disputes were sellted by seniour researcher.

Page 3: The data was extracted from the publications and structured using MS Excel v14. The evidence assessment is conducted with Oxford Centre of Evidence-Based Medicine (OCEBM). Since the meta-analysis is not feasable, the narrative analysis was rendered instead. There are numerouse mathematical evaluational metrics for the literature resources. From 2593-initial-search result only 14 articles are fully following the requirements. Not all authors diclose their conflict of interests. The data management and documentation is not consistant throughout the studies. The explanation are more or less consistent with all 14 papers. 11 Studies are from USA and the last three are from Canada, Colombia, and taiwaan. Dataset sizes vary from 500 to 302,300. The depth of the input data starts from seven and goas up to >1500. There is only one work which is done an external valisation of the DL model. The variaty of machine learning techniques was used in the overviewed submissions.

Page 4: The factors with the most impact on the predictions are: surgery specialty, expert prediction, primary surgeon, patient weight, and average surgery duration. The all studies, with one exception, demonstrated comparison of multiple ML approaches. Efficiency savings are in the discussion section. Only one publication presented the time efficiency saving. The tree-based MLs show the most accurate predictions. The ML is not always worth then DL, but usually by increasing the training sample size, the DL eventually stay in lieder's position.

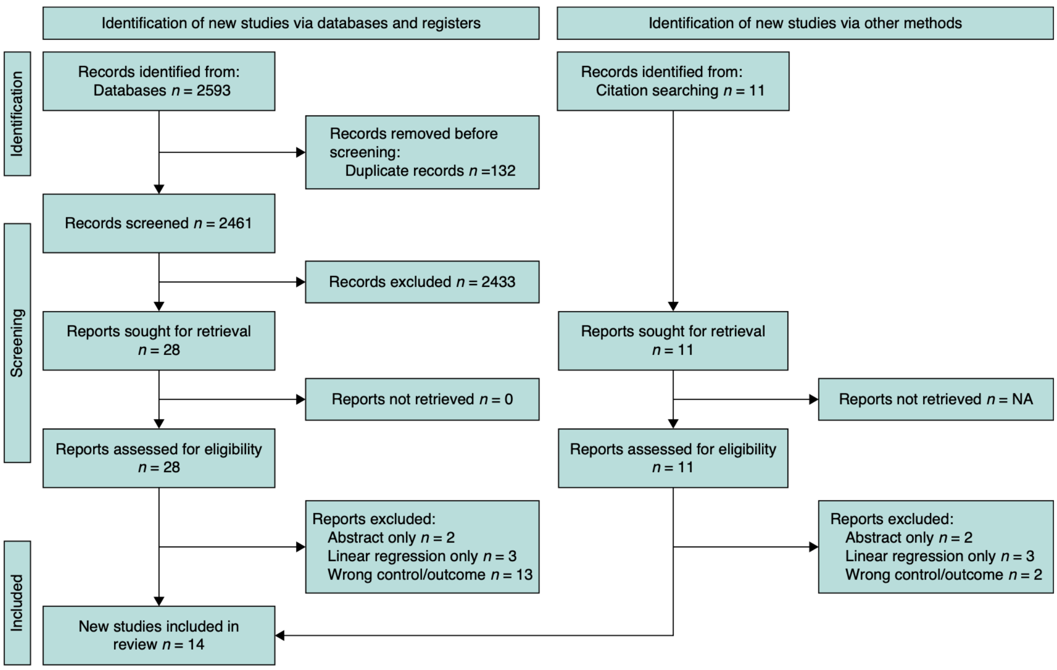


Figure 1.7: PRISMA diagram demonstrating the process of study selection, from screening to inclusion and the grey literature search (created using the online tool of Haddaway et al. (38)) from [3].

Page 5: The authors describe in more detail work by Jiao et. al. (19). The most common critarias:

- primary surgeon,
- historic average surgical duration,
- the experience of the surgeon,
- procedure name,
- the number the procedure lies within the list,
- type of anaesthesia,
- duration of the case,
- patient BMI,
- patient age,
- ASA score,
- patient sex,
- patient co-morbidities,
- anaesthesia provider (consultant/junior).

The clearing the medical records from redandant critarias helps reduce noise. Also, quality of the recording metters to the prediction outcome. ASA has lower importance than patient weight. Specific case of ML failure for correct prediction. The large predictions errors can significantly disrupt the hospital flow. Average OT costs in USA fluctuates from $22 to $133. The ML tend to ignore overruns in the surgery duration prediction. Abbas et al. (40) managed data in a way that provided generalise approach for the USA. The cleaning of datasets with missed fields have not been addressed in several studies. It is not enought to train on the dataset less then 1000, and large datasets is a must. There are numerous publications which are probably not generalisable.

Page 6: There is sparce number of ML implementations. There are only 14 accepted studies which may indicate challange to conduct sufficient scientific report in this field. The implementation and maintanance of the ML models require coordination from parties with divarce background. The AI policy is not evolved enough. There are requirements for efficient ML usage, such as tachnical aspects and motivated human resources. Also the surgery duration prediction is not the only way of applying ML. Raising multiple general musts. The ML/DL are more optimal way of the surgery duration prediction, but there is not enough work done for proper injection of the technology into hospital's workflow. The authors provide the authors' contribution section.

1.4 SR01TN18

1.4.1 Meta

Title: Surgery case scheduling in a multistage operating room department: A literature review

Rank	Grasp	Grade	Type	Outcome	Domain	COV19	CoI	DB
5	80%	F	A	-	S	No	-	-

Table 1.4: Reference's metadata

1.4.2 Summary

Marwa Khalfalli demonstrated the work with an unclear structure and objectives. There are no supportive visuals in the text. The study is hard to read and comprehend due to the ever-changing narrative. The author presents an unknown principle of two-stage scheduling: the first stage is a surgery case allocation, and the second is sequential scheduling. I **do not recommend** using this paper as a guide for research.

1.4.3 Reading

Abstract: The operating theatre scheduling is a complex problem which involves medical personnel and other resources. The surgery case scheduling in a multistage operating room department is presented in the work.

Page 1: OR management is one of the most important spheres in a hospital. Two-step scheduling process includes allocation and sequencing of ORs. Two steps are considered as separate combinatorial problems. OR department consists of Public Health Unit (PHU), OR, and PACU. There are three operative phaces.

Page 2: Intraoperative phace is the core of the surgery operation which requires multiple resources. In post-operative phace, the patient is transfert either to PACU or ICU. PACU may become a bottleneck of the surgery operation flow. ICU is closelly connected to OR utilisation and patient satisfaction level. Further an example in the case study was given and the integration scheduling introduced. More of the literature review summaries in the following paragraphs.

Page 3: In the left half of the page the author dives vague details regarding the two-stage operating room department particualrly the proposed problem description.

The right half eliberates more on the second stage of the scheduling process and presents more summaries of the existing studies.

Page 4: Many not coherent summaries of the different scheduling models.

Page 5: Introducing studies in the multi-objective scheduling.

Concusions: There are three concluding ideas: more considerations should be put into downstream and upstream untis; general thoughts on two the most important critarias such as overtime and utilisation; and highlights some new design. (what new design?)

1.5 SR02GB23

1.5.1 Meta

Title: Fractured systems: a literature review of OR/MS methods applied to orthopaedic care settings and treatments

Rank	Grasp	Grade	Type	Outcome	Domain	COV19	CoI	DB
4	87%	A	A	P	B	Yes	No	No

Table 1.5: Reference's metadata

1.5.2 Summary

Matthew et al. presented the first quantitative taxonomise review of the Operation Research and Management Sciences for Orthopaedic care services. One of the motivations for the review compilation is the ageing of the world's population, meaning more and more people will require special care. The authors searched resources in the Scopus database and produced the selection process and additional rounds of the search (back search). The authors searched by six categories in 2021 from Clarivate Jornal Citation. To analyse the extracted papers, the studies were classified by location, funding status, care area, injury location, JCR categories, implementation stage, research aims, and solution approach. The compelling visualisation of the data was shown to support the arguments. Finally, the need for further research was stated, and the limitations of the current literature review were highlighted.

1.5.3 Notes

- Focus on the rate of people in the world aged above 60 years.
- Has advanced searching techniques (pp7-8)
- The second work which mentions Medical Subject Headnings (MeSH)
- Six categories in the 2021 Clarivate Jornal Citation Report (JCR)

1.5.4 Reading

Abstract: The healthcare management is challanged with Earth growing population size and consequences of the COVID-19 pandemic. This literature review conducts a structurate overview of 492 publications in the field of Operational Research and Management Science applications. The authords of the review found a research gap and addressed it in the work.

Objectives / 1st page: The aim is to quantify and taxonomise the current state of the OR/MS approaches implemented in orthopadic department.

Page 2: There have not been direct guidances how OR/MS applied in the practice to optimise ortophedic departments prior to this review. Matthew Howells et al. [4] summarised some other literature reviews and concluded that for the best of their knowlesge there are no literature review on OR/MS from the perspective of orthopedic health care services.

Page 3: The reviewd papers are classified into three contexts: general, medical, and methodological. The studies for review were searched accross 6 categories to have diverse perspective on the OR/MS:

- Health Case Sciences & Services (HCSS);
- Health Policy and Services (HPS);
- Industrial Engineering (IE);
- Medical Informatics (MI);
- Operations Research and Management Sciences (OR/MS);
- Orthopedic (T&O);

The authors also define three types of data sources:

- Primary data - collected by researchers themselfs;
- Secondary data - collected by third parties and used by researchers;
- Expert opinion - generalisations on the public research with no direct access to the research data;

(i) Clarivate Journal Citation Reports category
(ii) Year of publication
(iii) Data source
(iv) Level of implementation
(v) Continent of application
(vi) Funding status

Figure 1.8: List of data extracted from the reviewed studies in [4].

Page 4: The research implementation is categorised into theoretical, conseptualised, and implemented works. The origin and the funding status of the reviewead research are included in the scope of this work. The orthopeci healthcare services are segmented on the smaller groups defined by the type of the illness by longtitude and the bodybart it effected.

Page 5: On this page the authors dive into more segmentations and classifications of the studies by the type of caregiver and environment (primary, secondary, tertiary, community, patient progression), by hospitalisation type (assignment, inpatients, surgery, post-surgery, rehabilitaion, follow-up) and by scope (clinical, department, or hospital).

Page 6: Further classtering of the research is defined by the healthcare funding providar (patient, provider, societal), by research aims (evaluation, forecasting, improvement), by algorithms applyed (Decision Analysis, Graph Theory, Heuristics, Markov, Multi-Critaria Decision-Making (MCDM), Optimisation, Queueing Theory, Soft OR, Statistical Analysis). The last classification is not not exclusive the approach can be both the delphy algorithm and an optimisation.

Page 7: There are three more approches of the OR/MS research grouping: by outcomes (cost, health, time), by functional area (Bed Management, Capacity Planning, Cost Analysis, Cost-Effectivenes Analysis, Cost-Utility Analysis, Expected-Valye Decision Analysis, Health-Unity Analysis, Location Planning, Manufacturing, Medical Decisions, Medical Simulations, Patient Scheduling, Risk-Benefit Analysis, Staff Utilisation, and System Design and Planning), and by planning decision levels (strategic, tactical, and operational which is futher segmented into offline and online scheduling). For searching the publications the Scopus database was used. The Appendicies A an B shows the searching terms and requests.

Page 8: This page present an advanced searching techniques and the proces of screening the 1,936 paper to 14.88% for the full text review and 2.14% in the final analysis.

Page 9: Here the authors explain the next steps for literature search such as back search using works in the initial search (Appendix C).

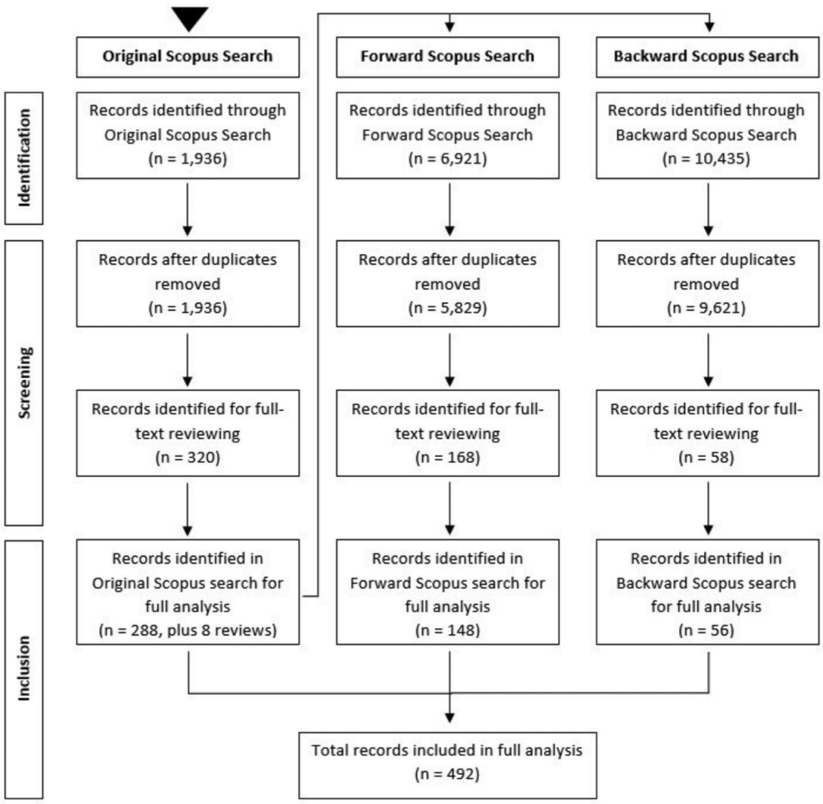
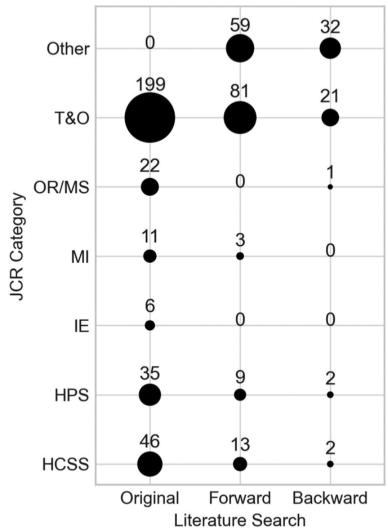


Figure 1.9: Flow diagram of the literature search in [4].

Page 10: The authors answare questions Who, When, and Under which surcumstances the model was developed and published.

Page 11: Literature analysis by the search type and the funding.



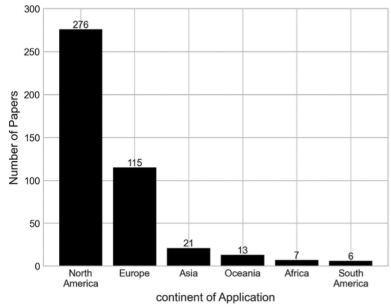


Figure 5. Number of papers by their continent of application.

Figure 1.10: Literature search analysis in [4].

Page 12: On this page the analysis of the papers by groups mentioned earlier.

Page 13: In this part there are more quantitative analysis of studies by care area and number of secondaty/tertiary pathways.

Page 14: Here the thoughts and answares to why the computational methods for orthopedic techniques have been developed.

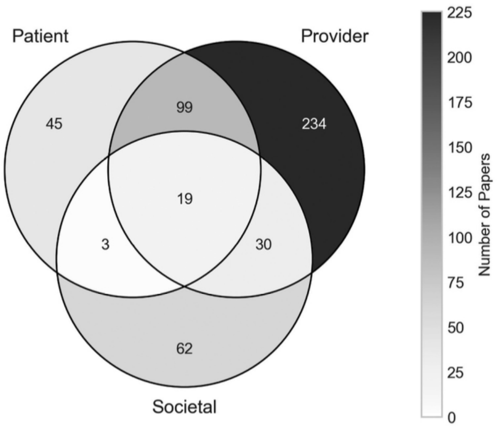


Table 1. Number of papers by their JCR category and planning decision level.

	Strategic	Tactical	Operational (Offline)	Operational (Online)
HCSS	7	3	0	0
HPS	11	5	1	0
IE	1	2	3	0
MI	2	1	0	0
OR/MS	11	8	5	2
T&O	1	1	1	0

Figure 1.11: Fundings and JCR category analysis in [4].

Page 15: The authors analysethe papers research aims, research outcomes, and number of papers with the real world implementation (which is less then 5%).

Page 16: The count of papers in each group by data type was analysed in this part of the review.

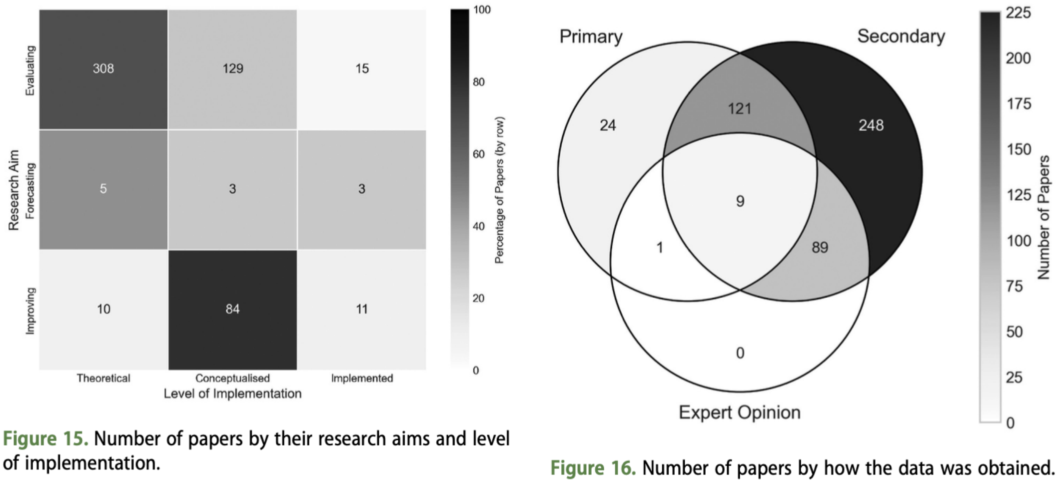


Figure 1.12: Research aim-implementation chart and types of used data chart in [4].

Page 17: On this page the developed aproaches have been quantified by number of papers.

Page 18:

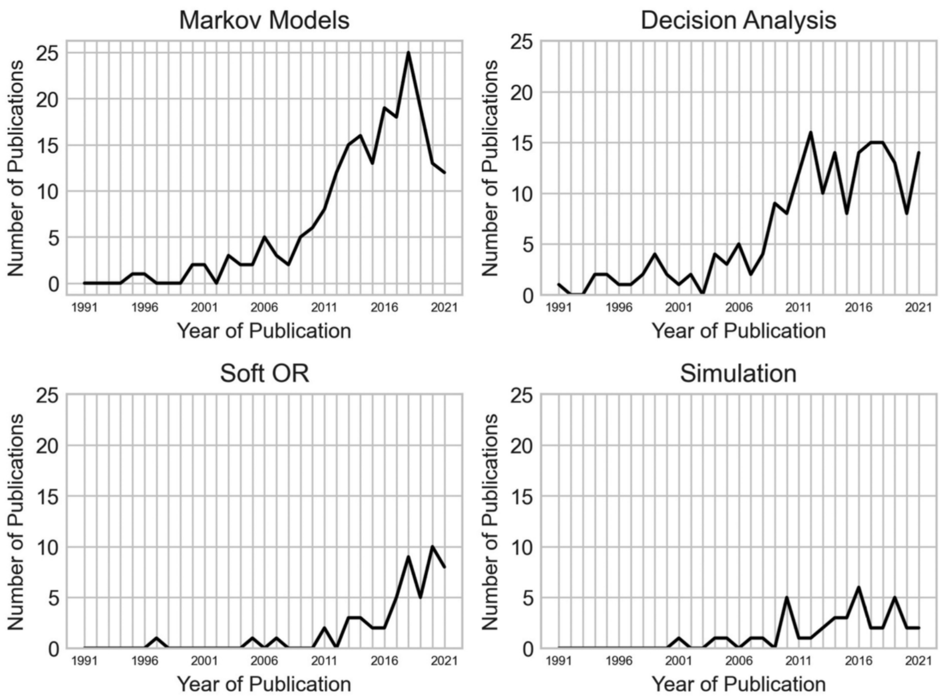


Figure 1.13: Trends from 1991 to 2021 from [4].

Page 19:

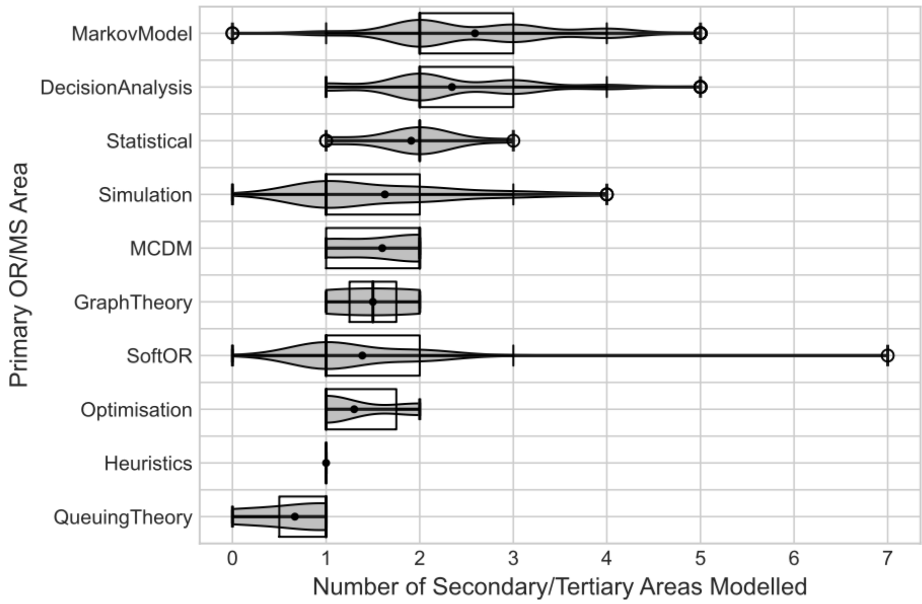


Figure 1.14: Number of papers by their primary OR/MS method area and level of implementation from [4].

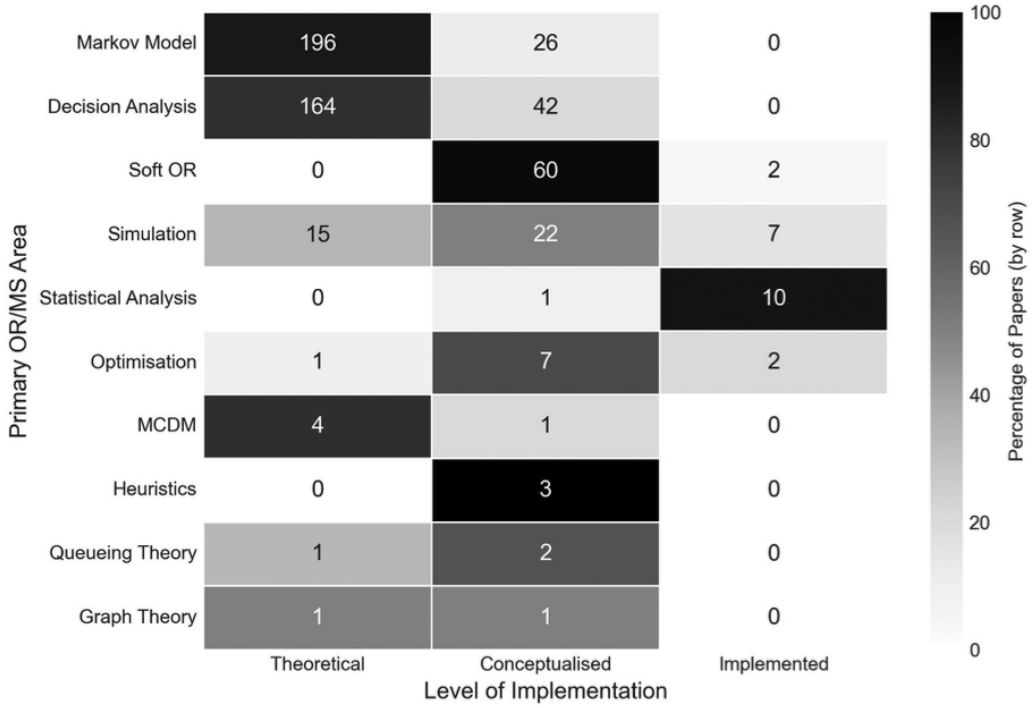


Figure 1.15: Distribution of the number of secondary/tertiary care areas modelled by each primary or area from [4].

Page 20: Here the authors focus on the different type of simulations and their efficiency. Next the discussion on the work is introduces and the authors hihglighted the limitations of the work in using just Scopus database with no concern to Medline and PubMed databases.

Page 21: The authors organise the materials in CSV filem Jupyter Notebook and Zenodo for research replicability. Next there are reflections on the frequency of the OR/MS research in the different regions of the world and on the trends in different categories.

Page 22: At the start of this page the non-resultive search and some drawbacks were discussed.

Conclusion: Matthew et al. summariese the current review in further points: the whole pathway modeling, capacity planning, optimisation, simulation, and queueing theories, mix-methodology, model implementation, addressing population ageing issue. These points are directions requiring further research.

1.6 SM01US23

1.6.1 Meta

Title: Ensemble Learning for Addressing Class Imbalance in Cardiology Appointment Scheduling and Overbooking

Rank	Grasp	Grade	Type	Outcome	Domain	COV19	CoI	DB
5	87%	B	A	P	A	Yes	-	Yes

Table 1.6: Reference's metadata

1.6.2 Summary

Roya Agharifar, Greg Servis, and Mohammad Khasawneh demonstrated an Ensemble Learning Prediction Model for no-show appointments in the radiology department with consideration of patient demographic data, medical records of previous appointments, and weather records. First, the authors analysed and reflected on existing studies. The medical data is represented by one year of EPIC Clarity Medical Records, and the weather records are taken from the National Centers for Environment Information, 2022. The cleaning, preparation, balancing, and analysis of medical data were performed. The prediction model consists of 3 types of algorithms bandle together by meta-model. The results yield up to 95.33% precision. In conclusion, the obstacles, research gaps, current research gains, and further work were underlined.

1.6.3 Notes

- EPIC Clarity Medical Record SQL database;
- No-show prediction considering weather;
- Weather data from National Centers for Environment Information (NCEI, 2022);
- Has the legend of dataset structure table;
- RepeatedStratifiedKFold splits classes in roughly the same distribution;

1.6.4 Reading

Abstract: The authors analyse the missing appointments in radiology through lense of the existing literature. The new prediction model was developed and evaluated for estimating the whether a patient will atend the appointment.

Objectives: The objective of this research is to analyse the patients behaviour of missing radiology appoinmtents and addressing the issue with prediction model.

Page 1: The introduction of the work provides motivation for efficient no-show prediction of the healthcare services. Overbooking is a contermeasure which can be applyed if there is a high risk of missng the appointment. By overbooking in risks of no-shows the utilisation of the medical resources is going to increase.

Page 2: Use machine learning technics to improve no-show prediction.

Page 3: There are multiple factors which deretmin likelyhood of missing the appointment by patients: forgetting, socioeconomic factor, location, miscommunication. The existing studies considering patients demographic data as well as historic data of previouse appointments for input in prediction models.

Page 4: In this page the authors show particular studies with the prediction models and analysis of the no-show reasons. Some works introduced that marial status, employment, employer, language, agen, and insurance are also critical factors which influance the prediction results.

Page 5: There are vfew strategies to reduce effect of no-shows. First, remind patients about an appointment, overbook days when the risk of the no-show is high, increase patients aweirness by phone calls and other medium. The critaria by which the no-show is quantified and evaluated differes from study to study in addition the factors of weather are not taken into consideration for the most part.

Page 6: The obsticles on the way of prediction model implementation is the posibility of biased decissions.

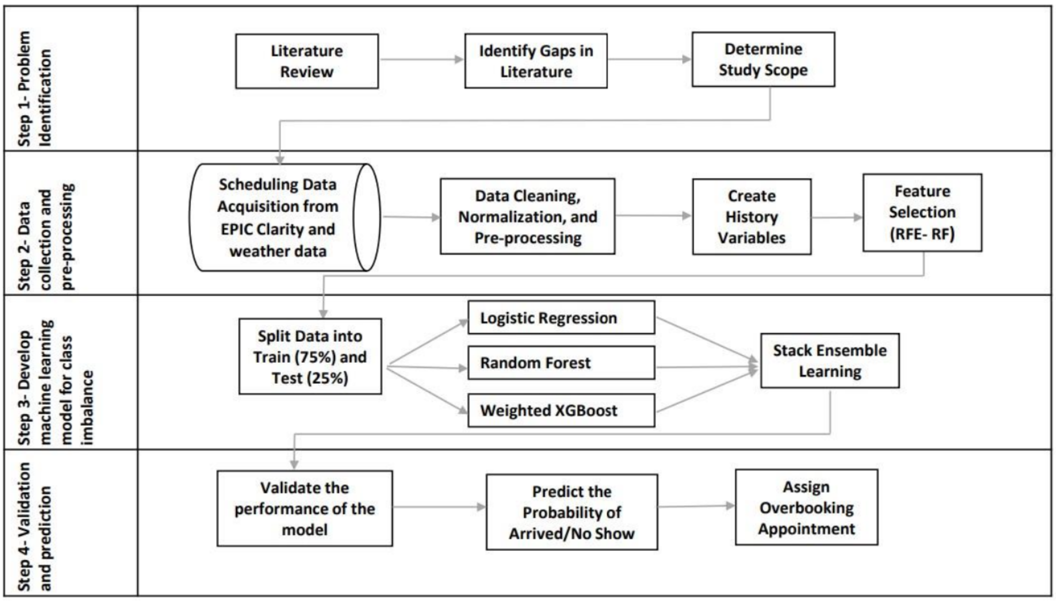


Figure 1.16: Research methodology framework from [5].

Page 7: The medical records and weather data were download from open source databases. In cardiology department at MSHS NYC from October 2021 to September 2022 there are almost 80,000 vists, from which 75.1% patients arrived and the rest are no-shows.

Page 8: The authors stated that the number of appointments influance the risk of missing the appointment (my thought is that probability theory when we have small and large numbers of visits can disrupt an interpretation of the data). Next the requred data for prediction is mined from medical and weather records and prepared.

Page 9: The start of this page is a legend table of dataset structure. Then the open hours for appointments and general analysis of the critaria-arrival are shown.

Page 10: The further the appointment is in advance the more likely that patient will cont come. In addition, older people tent to be more responsible and miss less appointments than younger people.

Page 11: There is comple opposite tendencies to eldery than to young generation. Elgery people are scheduling their hospital visits far in advance, when younger people have longer time spent with physicists.

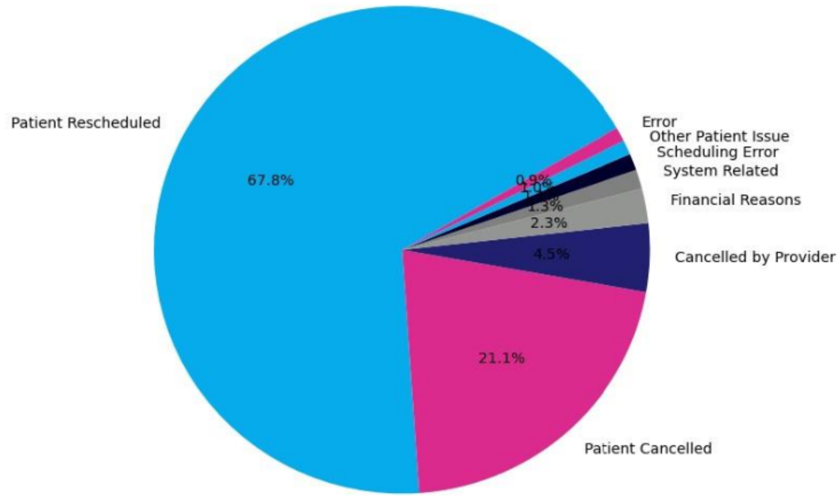


Figure 1.17: Research methodology framework from [5].

Page 12: The authors explained how they addressed uneven disttribution of classes in the dataset. Then the description of the prediction model was provided, which uses bagging (multiple models on different subsets). The data was distributer training to testing in the next way: October 2021 - April 2022 (75%) to May - September 2022 (25%) *(my consern here is that the tendencies in different seasons and even months can also different, which is not taken into account here)*

Page 13: The data samples were also balanced in rate of no-shows to arrivals.

Table 4: Model Performance

Model	F1 Score	Precision	Recall	Accuracy
Logistic Regression	85.87%	93.71%	79.54%	80.45%
Random Forest	88.87%	95.33%	83.23%	84.37%
XG Boost	91.66%	85.86%	98.30%	86.58%
Ensemble Model	92.30%	86.53%	98.80%	87.54%

Fig 11 depicts the ROC (receiver operating characteristic) curve related to the final model. The plot represents the true positive rate (sensitivity) against the false positive rate (specificity) at various classification thresholds. By adjusting the parameters to account for class imbalance, the AUC (area under the curve) of the ROC score was improved to 91% from 87%. This indicates that the model's ability to distinguish between positive and negative instances improved significantly after adjusting for class imbalance.

Figure 1.18: Preformance of the prediction model from [5].

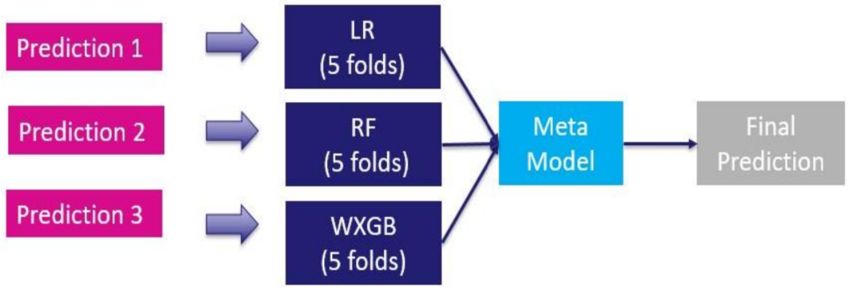


Figure 1.19: Architecture of the prediction model from [5].

Page 14: The trained model shows good results and balance between precision and recall. Most of the assumtion regarding the no-shows were prooved. Some metrics like distance, pm, and maximum temperature showed no effect on the prediction outcomes, so there metrics where removed from the model.

Page 15: The overbooking was estimated with consideration of no-show risk and patient's waiting time.

$$\text{Number of Overbookings} = \frac{\text{Number of appointments scheduled per day}}{1 - \text{prob(no-shows)}} \qquad (2)$$

Fig 12 depicts the actual volume (pink) and the predicted overbooking appointments (blue).

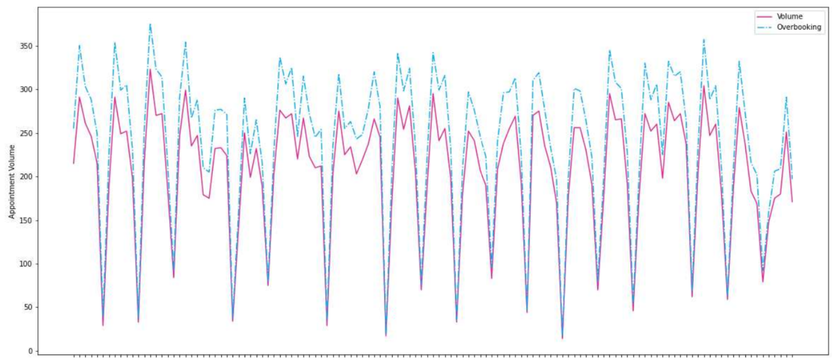


Figure 1.20: Overbook prediction in [5].

Conclusion: In the conclusion, the authors hightlight the importance of the prediction of appointment no-shows, performance of the developed model, need of practical implementation, advantages of overbooking, and possibility to connect morning and afternoon appointments in the way that the model could overbook at the morning to balance afternoon bookings. Last but not least the patients income level and race could be in benefit to the prediction model.

1.7 SR01MY22

1.7.1 Meta

Title: AI for patient scheduling in the real-world health care setting: A metanarrative review

Rank	Grasp	Grade	Type	Outcome	Domain	COV19	CoI	DB
5	90%	B	A	P	S	No	-	No

Table 1.7: Reference's metadata

1.7.2 Summary

Mohamad Khairulamirin Md Razali et al. conducted a classical literature review analysing the critical parameters of the Master Scheduling Surgery Problem. The authors' biggest emphasis lies in the optimisation component of the MSSP solutions. The seven known databases were searched for studies from 2000 to 2021, prioritising the publications between 2016 and 2021. What stands out from the other literature reviews is that the analysis methods and benchmarking methods have been discussed. As well as other literature reviews, the identified research gap was found to need more implementations of the schedulers in real hospitals and a lack of actual medical records for research. An unexpected suggestion was given regarding the hyper-heuristic optimisation models. The authors stated that hyper-heuristics have been successful and widely used for other optimisation problems. Still, no studies highlight the utilisation of the hyper-heuristic scheduler for the MSSP. Overall, this literature review has three most valuable points: a list of databases for further study search, benchmark approaches, and a new view on the hyper-heuristic methods.

1.7.3 Notes

- Literature databases: Scopus, WoS, Dimensions.ai, SpringerLink, ACM Digital Library, IEEE Xplore, and Google Scholar;

- Has solution evaluation methods: Sensitivity Analysis, Robustness Analysis, Model Variation Analysis, Pareto Frontier Analysis, Simulation;

- Shortsights: ignoring objectives, priority of objectives, ignoring uncertainty, assumptions in hospital practice;
- Challenges: Data Availability, Simulation vs Real World, Software Cost;
- What is hyper-heuristic?

1.7.4 Reading

Abstract: The Master Surgery Scheduling Problem (MSSP) assines the surgery cases to theatres, surgeons by specialty. In this literature review state-of-the-art MSSP problem have been analysed in studies from 2000 to 2021 focusing on the papers between 2016 and 2021.

Objectives: The work aims to overview the papers in the field of Master Surgery Scheduling Problem, identify trends and address the existing research gaps.

Page 1: The MSSP represents one of the desicion levels descriped in (5). There is still some missalignments in terminology and only few studies addressed the MSSP in details.

Page 2: Mohamad Khairulamirin Md Razali et al. enhpacise the difference between this and other literature reviews on MSSP by consentraiting on optimisation of MSSP. Then the questions of the research and methodology oitlined and the introduction to MSSP was presents.

Page 3: This page continues to explain MSSP desicion-makng flow together with more details on the gathered studies (Focus January 1, 2016 - October 22, 2021).

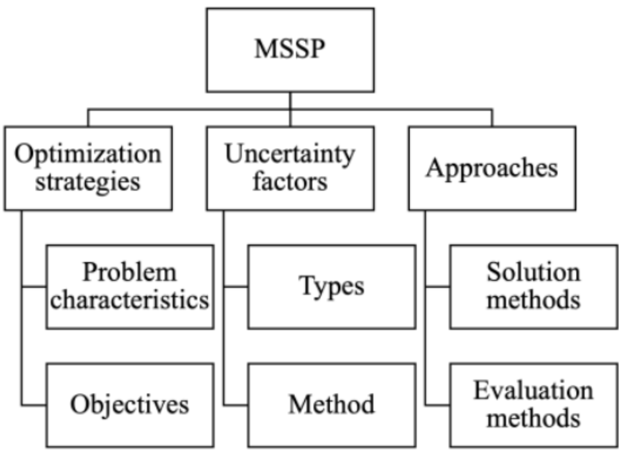


Figure 1.21: MSSP classtering in [6].

Page 4: The authors describe the searching process and databases used. Then a simple comparative analysis was conducted on the several works. At the end of the page, types of the surgery group were introduced.

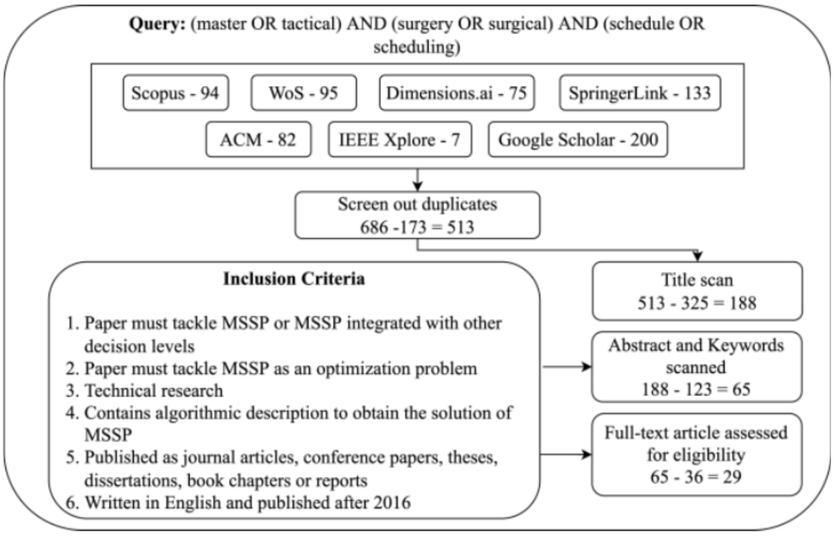


Figure 1.22: Quantitative summary of the literature search in [6].

Page 5: The page consists of table with reference-contribution-applicability-limitation content of the overviewed studies.

Page 6: Planning horizon and schedule cyclicity is described in general terms by referencing on the reviewed literature.

Figure 1.23: Studies distribution by the surgery group type and by planning horizon in [6].

Page 7: The objectives and constraints are indicated in the literature and quantitative summary on the objective functions is shown below.

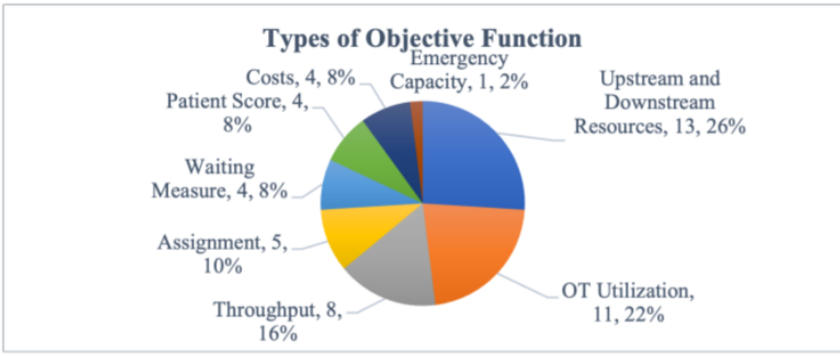


Figure 1.24: Studies distribution by the objective functions in [6].

Page 8: In this page the disctibution of works with unsertainty and general overview of papers with different solution approaches (optimisation, heuristics).

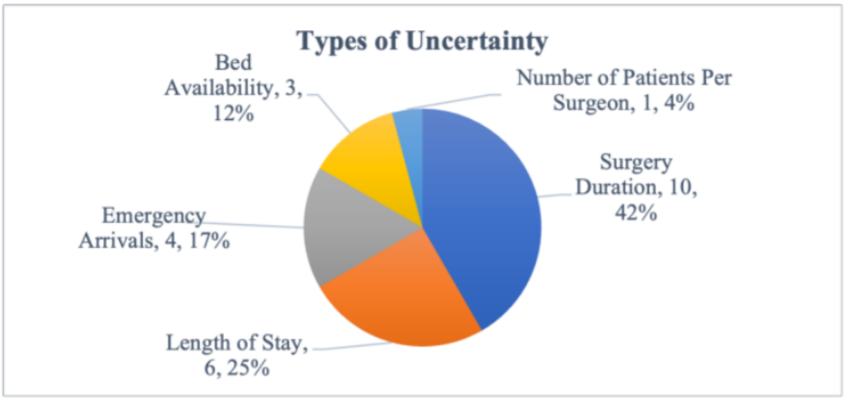


Figure 1.25: Studies distribution by uncertainty in [6].

Page 9: The authors summarise the evaluation methods into distribution pie-chart and the table containing the reference, algorithm name, benchmark approach, and results.

Page 10: Here the types of analyses used in the studies are presented as well at the obsticles or pure decissions made in the reviewed researches.

Page 11: The authors highlight importance of the real hospital records as well as the practical implementation of the proposed solutions. The consern is rased that the financial resources should also be spent optimaly for the MSSP solutions. In addition the suggestions regarding the scheduling cycles, uncertainty, computational complexity (hyper-heuristics), banchmarking.

Conclusion: The authors repeat goals from the introduction to this research and hihglight the analysis of the papers from 2000 to 2021 in respect of uncertainty, used data, implementation, and solution approaches to MSSP. There are still uncharted territory in diration of stratefies for optimising efficiency, multiple decision levels, MSSP complexity, and aspects which influance objectices usage.

1.8 SR01ES23

1.8.1 Meta

Title: Data science, analytics and artificial intelligence in e-health: trends, applications and challenges

Rank	Grasp	Grade	Type	Outcome	Domain	COV19	CoI	DB
5	93%	C	A	??	A	Yes	Yes	No

Table 1.8: Reference's metadata

1.8.2 Summary

The review work by Juliana Castaneda et al. [7] is a general overview of AI practices in healthcare and their implementation. It considers the development of AI solutions due to the COVID-19 crisis. The paper qualitatively summarises the machine learning methods in the scope of data development and some relation to the Internet of Things technology. The practical side of the work is in the methods used for quantifying the frequency of the word's appearance in the studies and the automatic topic extraction script. This work will benefit most newcomers in the crossfield of Artificial intelligence and healthcare who want to decide on the direction of their research.

1.8.3 Notes

- Non-negative matrix factorization (NMF). Diverse data inro meaningful topics.
- Data preprocessing + NMF + Python (scikit-learn library)
- Pyrthon cleaning data code `https://github.com/Julianac-j/NMF_ehealth`

1.8.4 Reading

Abstract: The development and application of the predictive models, and artificial intelligence in healthcare environment are hihglighted in this literature review. In addition the benefits for healthcare organisations will be discussed alongside the obsticles and complexities.

Page 2: Introduction to Big Data technology, Machine Learning, and Artificial intelligance comparing with the progress similar to arise of the Internet.

Page 3: The Big Data in scope of IoT Technology as well as IoT in Healthcare System were outlined in this page. The basic explanation of search methods for the literature and the structure of the article are presented next.

Page 4: Here is shown an exponantial increas in papers regarding the AI, e-health, and data science in Scopus and Google Scholar with Google Scholar in the lied.

Page 5: The authors mentioned the pandemic challenge and the responce in the scientific community to it. Also the non-negative matrix factorization was described with examples of implementation in the literature. In basic terms, this is method of extracting data from unstructured dataset into meaningful topics.

Page 6: Using Python clean the data, define the workd frequency and using NMF quantify the most common topics.

No.	Five-word set	Topic	References
1	learning, machine, deep, model, recognition	machine & deep learning for recognition	Shatte, Hutchinson and Teague (2019) Yu, Beam and Kohane (2018) Kavakiotis et al. (2017)
2	IoT, internet, things, devices, security	IoT devices security	Al-Garadi et al. (2020) Din et al. (2019) Makhdoom et al. (2018)
3	blockchain, technology, applications, consensus, research	blockchain technology in security and privacy applications	Chukwu and Garg (2020) Roy et al. (2018)
4	data, big, analytics, processing, medical	big data in healthcare medical analytics	Wang and Alexander (2020) Syed et al. (2019)
5	access, control, encryption, data, attribute	cloud and fog computing for privacy and security	Sun (2020); Dang et al. (2019) Mutlag et al. (2019) Puliafito et al. (2019)

Figure 1.26: Topic modeling results obtained with the NMF algorithm in [7].

Page 7: Next is the total number of the papers reviewed (403) and the numbers of the papers in the searching groups.

Page 8: Analisys of the e-health papers by the number of words.

Page 9: The description of the prediction models in e-health was descriped in this page.

Page 10: The studies with descriptive analysis was mentioned here.

Page 11: Some management computational tools for unstructured data are show in this page.

Page 12: Representing some data science arias such as data mining.

Page 13: Mentioning the dufferent areas of the Artificial Intelligance.

subfield	Year																				Total
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	
Deep learning	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	8	17	20	34	85
Reinforcement learning	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	2	3	3	5	15
Clustering	0	0	0	1	0	2	0	0	5	0	1	4	3	5	11	9	8	12	5	8	74
Data visualization	0	0	1	0	1	2	0	1	3	5	2	2	1	4	1	2	3	9	3	5	45
Artificial neural network	0	0	0	0	1	2	1	1	1	0	3	2	3	0	2	2	4	5	3	10	40
Natural language processing	1	0	0	0	0	0	1	1	1	0	2	4	4	3	3	2	3	9	4	5	43
Fuzzy logic	0	0	0	1	1	0	1	1	2	0	5	1	4	2	6	4	2	1	2	10	43
Bayesian networks	0	0	0	0	0	1	4	0	0	0	9	1	3	1	2	0	2	1	3	3	30

Figure 1.27: Number of e-health papers from [7].

Page 14: The authors intriduced a machine learning and the questions which arise when working with them.

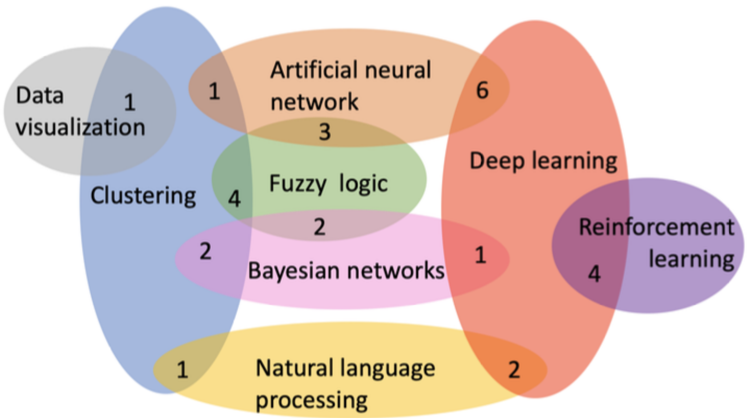


Figure 1.28: Number of e-health papers from [7] venn diagram.

Page 15: List of the papers which study or use machine learning techniques in e-health.

Page 16: Introduction of data mining, NN, and natural language processing AI.

Page 17: A particular applications of NLPs and best practisies in e-health for AI systems.

Page 18: AI in: medical care, diagnostics, personalised medical care, ...

Page 19: More AI applications in e-health: treatment optimisation, assistance or automated prescription, triage, surgery,pregnancy management.

Page 20: AI in general hospital care: demant forcastig, screening, ...

Page 21: ... epidemics prediction and flow analysis, fake news recognition.

Page 22: AI for healthcare management: resource forcasting and managememt, grug chain supply, medical services scheduling, ...

Page 23: ... facility allocation, preformance evaluation, brand management and marketing, finantial data, fraud detection, ...

Page 24: ... patient satisfaction. AI work in lab dor COVID-19 vacseen development...

Page 25: ... fluently transforms into AI tools to recognise fake news about COVID-19. Also the authors starts discuss other AI implementations...

Page 26: On this page the insights and obsticles in the e-health with IA are outlined. The main diractions of AI implementation are cancer treatment, depression, Alzheimer disease, heart failure, and diabetes. To get full benefits from AI technology we need to overcome the defencivness and the learning curve for the profesionals in the healthcare industry and learn how to implement the AI systems flawlessly.

Page 27: The Corona Virus crises gave a push for new data and analytical development. The deep learning models not just boost the performance of the healthcare services but also ensure the safety and integrity of the patient's data.

Page 28: This page is all about legal regulations on the organisational and governance levels.

Page 29: It is a need in setting people minds into all-sharing data to overcome the resistance barriar in sociaty. The next paragraph is about predicting and managing the future pandemics.

Conclusions: The conclusion is played around the nessasity of beter data analysis and collection, since the machine learning models are already advanced in respect to the quality and quantity of the data resources.

1.9 SR01NL22

1.9.1 Meta

Title: AI for patient scheduling in the real-world health care setting: A metanarrative review

Rank	Grasp	Grade	Type	Outcome	Domain	COV19	CoI	DB
4	95%	B	A	P	A	Yes	??	No

Table 1.9: Reference's metadata

1.9.2 Summary

This article presents a systematic literature review that covers the natural language process models for predicting healthcare-related events from textual data. Oscar Hoekstra, William Hurst, and Joep Tummers conducted a quantitative analysis of the existing literature in the field by 2022. The authors emphasise that they are not comparing the existing studies due to the unavailability of the unified criteria but explore the performance of the NLP models separately. The work is well structured, but what needs to be added is a discussion on the healthcare problems which can be solved or optimised by the NLPs.

1.9.3 Notes

- PubMed, IEEE and WebOfScience;
- Quality assessment method?

1.9.4 Reading

Abstract: The systematic literature review is summarising the results and show currnt efficiency of the Natural Language Processing models in the area of healthcare related event prediction. The authors used open access databases to retreave the corresponding studies. The current state of the research does not allow to make a comprehencive comparison of the existing solutions.

Objectives: This research aims to investigate a medical event prediction solution with textual data on the input.

Page 1: There are a lot of textual medical records which requre a lot of time and resources to structure in order to get some usefull insights. The current research looks into the NLP prediction models which use these type of records to predict healthcare related events.

Page 2: In the begining of the page, the authors formulate three questions for the research: What is the state-of-the-art? How do ML models predict? What ML models are sued? Then the outline of the paper is presented. The rest of the page describes the methodology methods used to search and screen the studies related to the topic.

Page 3: The stages of the literature analysis are outlined and after the applying the selection methods the 38 articles have been selecet.

Study exclusion criteria.

No.	Exclusion criteria description
EC1	Papers not available in English or Dutch
EC2	Papers without full text available
EC3	Duplicate publication from multiple sources
EC4	Papers that do not describe the use of ML in the abstract
EC5	The ML application described does not focus on textual data
EC6	No event prediction, occurrence prediction, or result of treatment prediction
EC7	Papers that are literature reviews.

Table 2
Study quality assessment criteria adapted from Kitchenham et al. [17].

Nr.	Quality assessment question
vQ1	Are the aims of the study clearly stated?
Q2	Is the dataset used in the study clearly described?
Q3	Is the underlying mechanism of the method clearly described?
Q4	Is the method reproducible?
Q5	Does the conclusion describe the main findings?
Q6	Are limitations of the approach mentioned?
Q7	Are accuracies related to the methods and results mentioned?
Q8	Are negative findings presented?

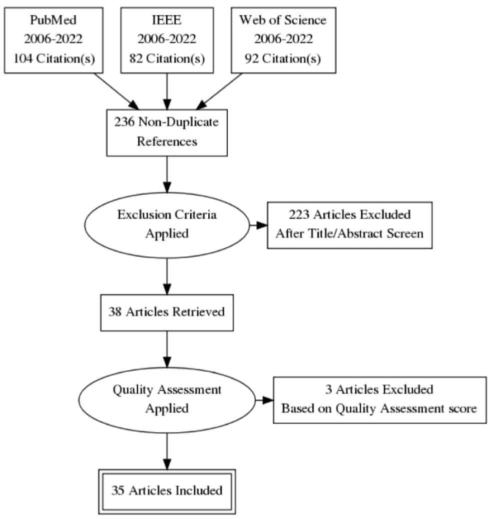


Figure 1.29: Selection critaria in [8].

Page 4: The quality evaluation results show that only one of nine papers is qualified. Also the performance critaria were presentd for the researched NLP models.

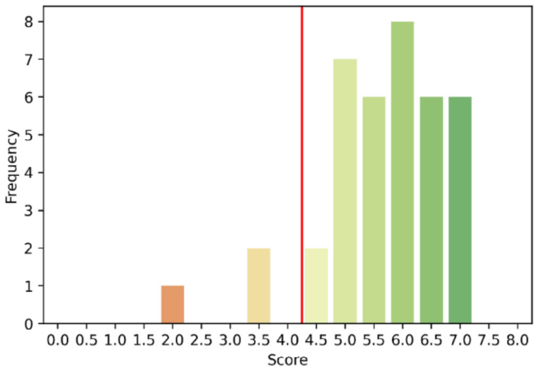


Fig. 4. Quality assessment scores by frequency. Cut-off score = 4.0.

Table 3
Results of study exclusion by database source.

	PubMed	IEEE	WebOfScience
Exclude	81	73	86
Include	23	9	7
Percentage (Include)	22%	11%	8%

Figure 1.30: Quality evaluation in [8].

	Total	F1	Precision/ PPV	Recall/ Sensitivity	Specificity	Accuracy	NPV	ROC AUC	PR-AUC	MAE
Used in n articles	28	14	13	17	8	9	3	10	2	2
Total uses	121	88	74	81	10	26	5	34	5	4

Table 5
Number of times each machine learning method was used in the selected studies. Unique uses are counted as the number of studies that used the method.

ML method	Unique uses	Total uses	ML method	Unique uses	Total uses
Tree	5	6	RNN	3	5
SVM	9	16	Gradient boosting	1	1
BERT	2	2	RF	4	5
word2vec	3	3	Elastic net	1	1
USE	1	1	LDA	1	1
KNN	1	1	SVC	1	1
LR	5	6	Rule-based	1	1
LSTM	4	5	DNN	1	2
BERT + LSTM	1	1	HAN	1	1
ML	4	8	CRF	2	8
LASSO	2	4	FOIL	1	2
XgBoost	1	1	LexRank	1	8
NN	1	1	NRT	1	8
SGD	1	1	DCA	1	8
ULMFiT	1	2	Naive Bayes	1	6
CNN	4	9			

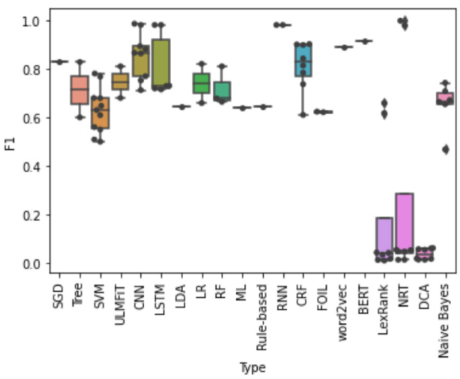


Fig. 5. F1-score of the types of methods in the selected studies.

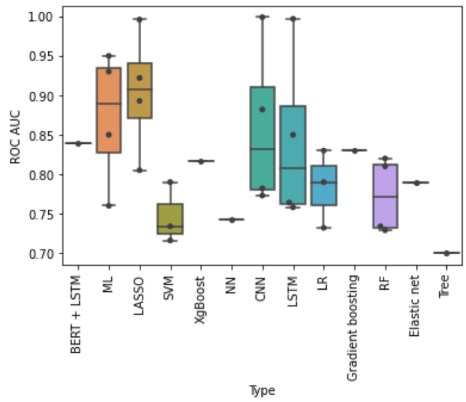


Fig. 6. Receiver operating characteristic area under the curve of the types of methods in the selected studies.

Figure 1.31: Method used distribution from [8].

Page 5: The SLR is the first in a kind according to the authors of the work. An interest in NLP technology is growing which is shown by the high publication rate for the last 5 years in comparison to earlier publications.

Page 5: There is no ultimate supaeiar MLP model which will outperform the other solutions. There NLPs which can perform using just textual data, but for most cases the additional structured data is used to enhance the results. Till the end of the page the authors summarise the scores of different models and overal quality of the studies by the number of selected publications.

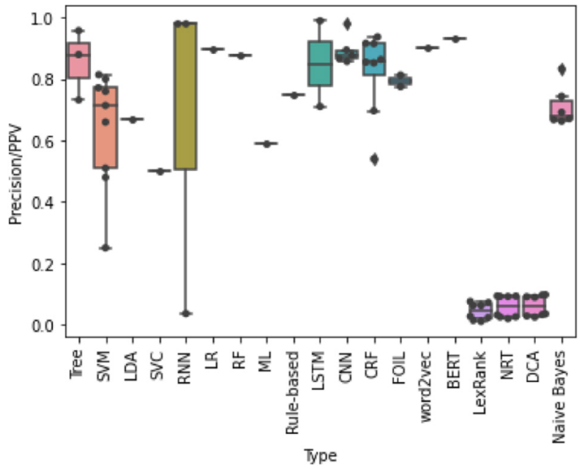


Fig. 7. Precision or PPV of the types of methods in the selected studies.

Figure 1.32: Precision or PPV of the types of methods in the selected studies from [8].

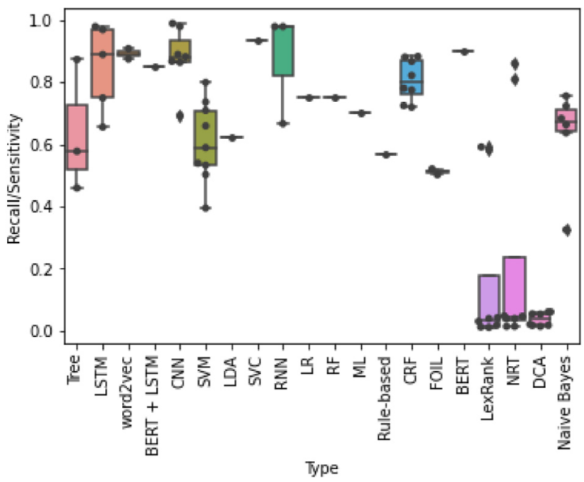


Fig. 8. Recall or Sensitivity of the types of methods in the selected studies.

Figure 1.33: Recall or Sensitivity of the types of methods in the selected studies from [8].

Page 6: There are multiple obsticles to the conducting this systematic literature review. First some studies present unexpected unrealistic results lik F1-score above. Another challenge were studies which do not evaluate their models.

Data extraction form to extract general information about the articles.

No.	Extraction element	Contents
General information		
1	DOI	
2	Title	
3	Authors	
4	Year of publication	
5	Repository	
8	SLR category	☐ Include ☐ Exclude
9	Notes about selection	
Description		
10	Keywords article	
11	Database terms	
12	Link	
13	Case study application	
14	Goal	
15	Approach	
16	Techniques	
17	Tools used	
Evaluation		
18	Quality assessment	Q1: Q2: Q3: Q4: Q5: Q6: Q7: Q8: tot:
19	QA notes	

Figure 1.34: Extructed data from publication in [8].

Conclusion: In the conclusion the authors hihglighted stable good performance of the Neural Network models and also BERT models. The all outilined in the introduction aims were reached and the suggestion for the future research is to standardise the evaluation criteria for the NLP models.

1.10 SR02NL23

1.10.1 Meta

Title: Integrated Planning in Hospitals: A Review

Rank	Grasp	Grade	Type	Outcome	Domain	COV19	CoI	DB
5	96%	A	A	P	B	Yes	??	No

Table 1.10: Reference's metadata

1.10.2 Summary

Sebastian Rachuba, Melanie Reuter-Oppermann, and Clemens Thielen conducted a literature review considering hospital-integrated planning. The authors rendered a standard systematic literature review with taxonomy analysis. By the author's narrative, integrated refers to the interconnection of hospital resources and the mutual influence of different aspects of healthcare related to medical care planning. The three levels of integration were defined, and among these three levels, the reviewed studies were distributed. The integration of hospital planning was discussed, including the hospital levels of strategy, planning approaches, research objectives, and connections between research criteria. The arguments were supported by graphical visualisation of the analysed data. The main conclusions of the work are that the trends are shifting toward medical stuff from operating theatres, and there is a possible increase in papers which investigate healthcare services with no direct interaction with patients, such as pharmacy and OT cleaning.

1.10.3 Notes

- Health departments disconnection;
- Vertical/ horisontal integration;
- `www.webofscience.com`

1.10.4 Reading

Abstract: This literature review is about an integrate operating theatre scheduling. The abstract begines with the starting point of medical resource scheduling in scientific literature which is year 1950. The work proposes a taxonomy analysis of the current state of operating theatre scheduling research.

Objectives: Research the existing literature in scope of healthcare integrated planning.

Page 1: The importance of healthcare system in modern world can be seen in the budgets issues for the healthcare need in Europ which is almost 11%.

Page 2: The ever increasing demand of the healthcare services can be regulated with the improvement of the medical resource management. One of the obsticles is disconnection between departments even in the same hospital. The efficient method to ensure interconnection between various departments is to use horizontal and vertical integrated in hospitals.

Page 3: The structure of the paper as well as the methods used for searching the literature were outlined on this page.

Page 4: The authors did not limit the approved for in-depth review papers by the year of publication. For the detailed review 318 potential studies were selected.

Page 5: This page introduces the classification of the papers by their level of integrated. There are three levels of hospital planning integrated.

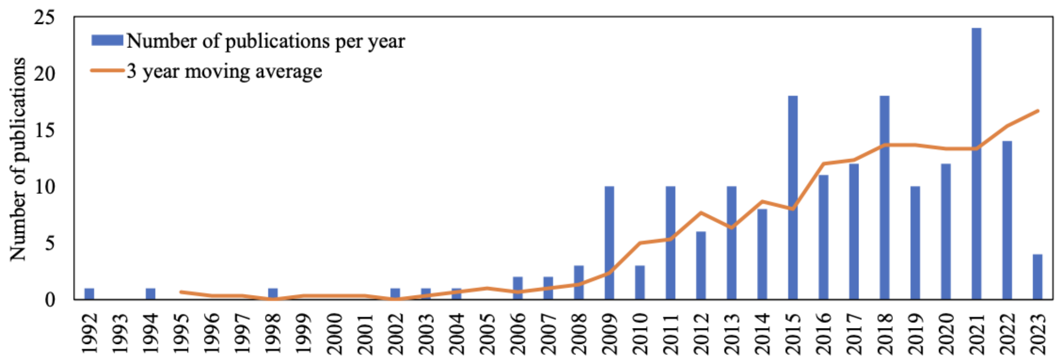


Figure 1.35: Number of publications over the years from [9].

Page 6: On this page, the authors explaine the connection between all three level of integrated and how does it interpreted into the operating theatre planning and scheduling.

Page 7: The second level of integrated planning is the least investigated and the first and the third levels have been interchanbaly in the lead by number of publications from year to year. Another tendency is in the number of tactical and strategical planning. The hbroader the perspective the smaller number of papers have looked into this, and it is true for all three levels of integrated.

Page 8: Here the authors list a medical resources that are objectives of the scheduling and planning.

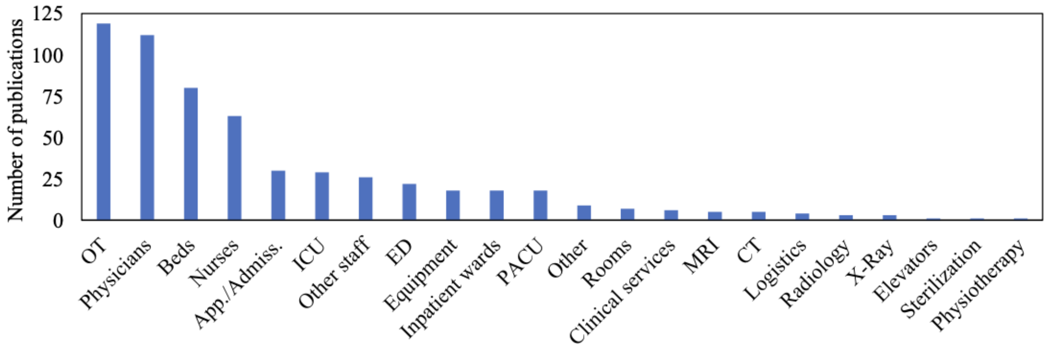


Figure 1.36: Objective trends in [9].

Page 9: Operating theatres are most ofteen considered as a promary resources.

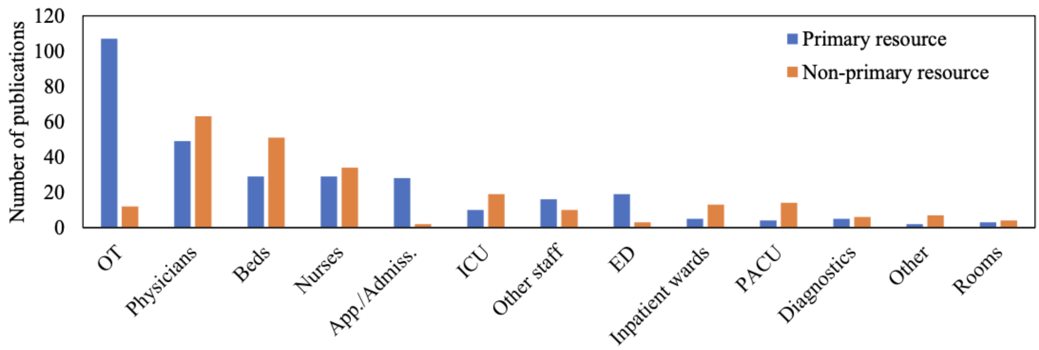


Figure 1.37: Objective trends as primary or secondary critaria in [9].

Page 10: The authors looked into the combinations of the resources in the literature.

Combined resources (columns) / *Primary resources* (rows)

	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 1.38: Resource combinations from [9].

Page 11:

Combined resources (columns) / *Primary resources* (rows) — Level 1

	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	

Combined resources (columns) / *Primary resources* (rows) — Level 3

	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	

Figure 1.39: Resource combinations by livel of integraion planning from [9].

Page 12: Here was stated that the focus from OT planning and scheduling shifts toward the medical staff members with increasing of the integrity of the model. This page lists the solution approaches to the different levels of integrated planning. The combination of approaches gained its popularity amoung researchers.

Page 13: The authors segment the planning solutions into three categoris: optimisations, symulations, and other. The flows of the number of publications amonng years have been provided.

Page 14: One unexpected tendency is regarding stuff related planning and optimisation panning approaches. The optimisation methods are used less for stuff and more for all other objectives, where stuff related problems are usually solved by simulations or other methods.

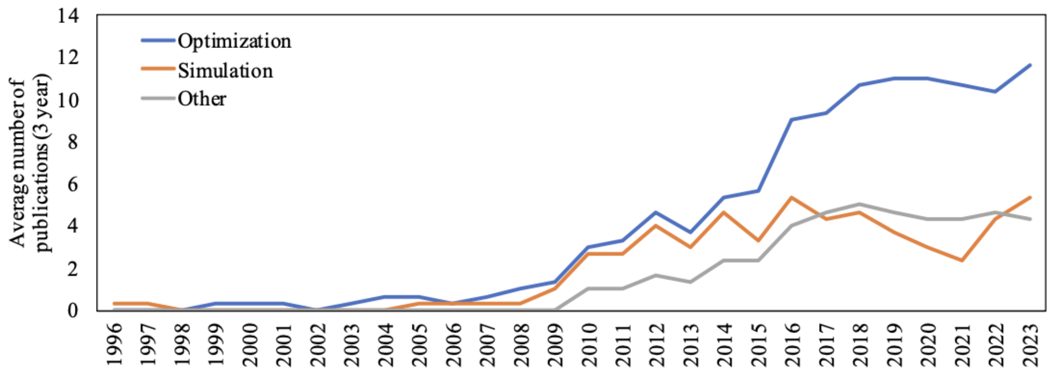


Figure 9: High-level overview of methods over time (3 year moving averages).

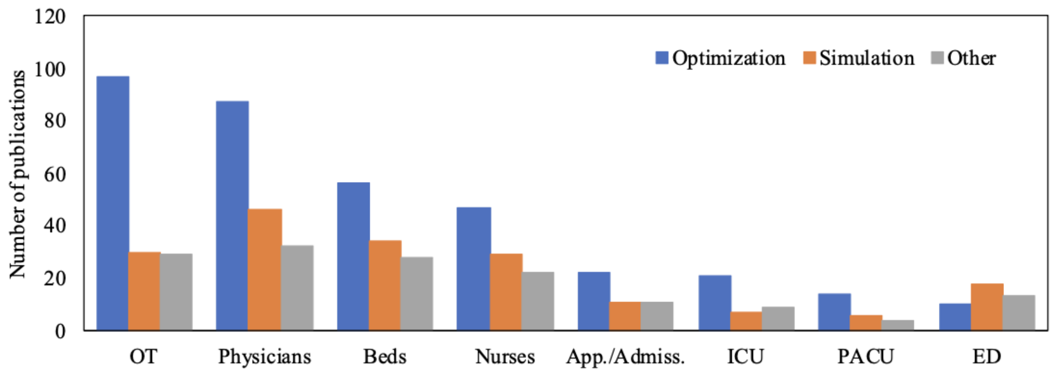


Figure 1.40: Publication trends between 1996 and 2023 from [9].

Page 15: In this page more in-depth analysis of the trends in relation to levels of integrated was conducted.

Page 16: Here is the final thought about general features of the studies, and the analysis continues to a practical side of the medical resource scheduling and planning which consideres uncertanties.

Page 17: More analysis regarding the models with uncertainties.

	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)

Figure 1.41: Studies that considered deterministic, stochastic, robust, and online in relation to the level of integrated in [9].

Page 18: The reviewved works offer a veriaty of different uncertainties in the healthcare envorenment. Only a minority of the reviewed studies implement their models into real hospitals. Thera also other approaches to evaluate the developed scheduling approach.

Page 19: Basically in this page tha authors describe the chart below ephacising that the are not many practical implementations of research, which indicates that journal publishers does not care about this aspect too much.

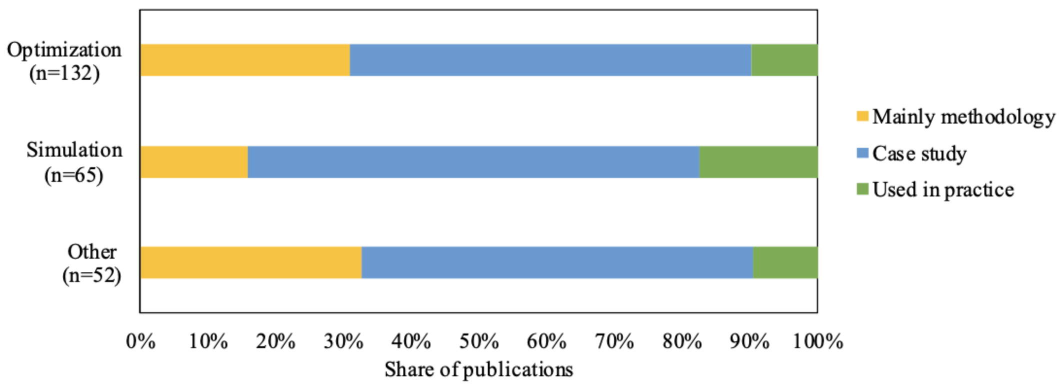


Figure 1.42: Distribution of theoretical work, case study, and implemented research for optimisations, simulations, and other approaches in [9].

Page 20: Here is an introduction of three departments depend on the patient stage of the healthcare flow: pre-hospital departments, during-hospital departments, and post-hospital departments.

Page 21: The department interconnections.

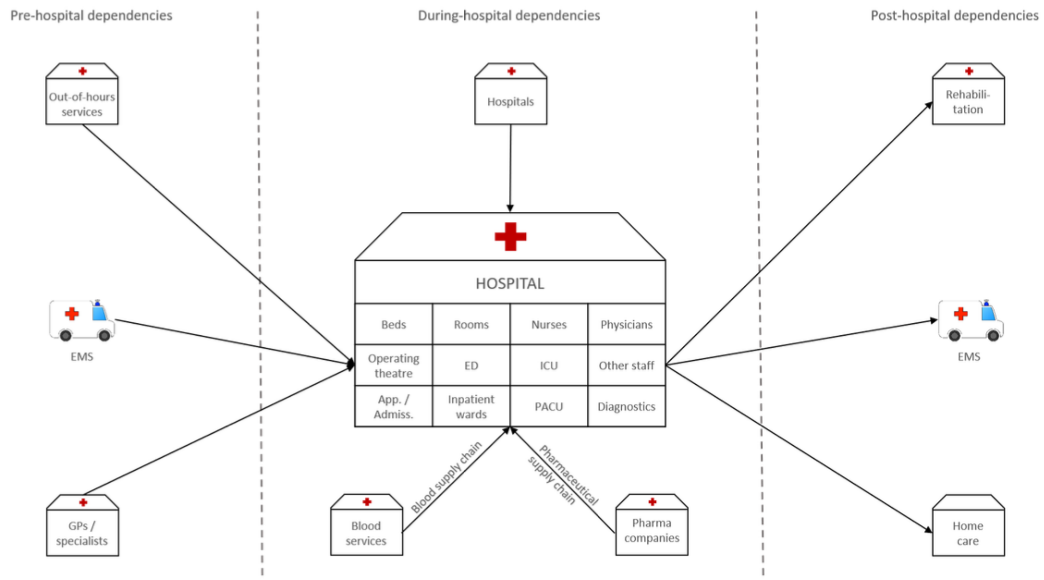


Figure 1.43: Hospital departments from [9].

Page 22: The main resources in during-hospital department and bottlnecks in post-hospital demartments were discussed on this page.

Page 23: The trends show that if consider nurses and phisicians ander one term medical staff the number of publications starting from 2010 exceeds the number of publivations for OT. Nevertheless, OT still remains the most frequently considered primary objective in the medical resource scheduling research.

Page 24: There is still lack in studies which condidering uncertainties. Tha authors predict that it possibly will change in the near future, because the number of related work is growing. Implementation of the research findings on practice is also not frequent fenomena.

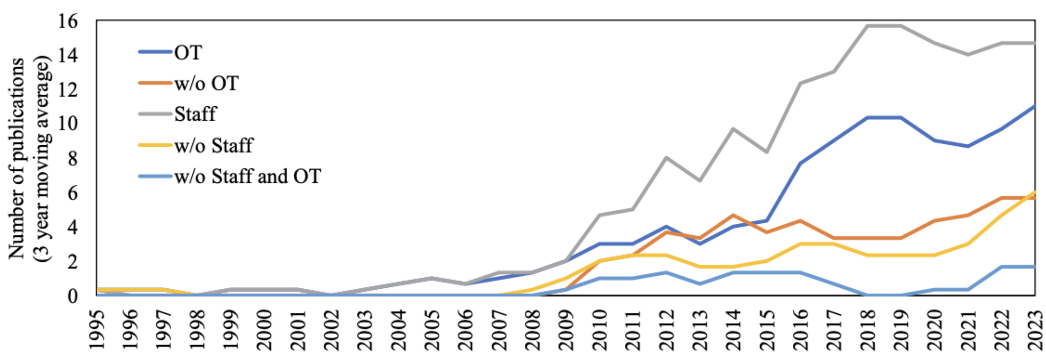


Figure 1.44: 3-year moving averages of the numbers of publications that do / do not consider OT or medical staff. from [9].

Page 25: The ephasis in the research gap lies on studies wich do not interact with the patient directly (pharmacy for instance) and also onto medical staff oriented research.

Page 26: 1. Planning which does not involve patients diractly; 2. Medical staff choreography; 3. Simulation studies; 4. Practical implementations.

1.11 SR03NL12

1.11.1 Meta

Title: Taxonomic classification of planning decisions in health care: a structured review of the state of the art in OR/MS

Rank	Grasp	Grade	Type	Outcome	Domain	COV19	CoI	DB
4	94%	A	A	P	B	No	??	No

Table 1.11: Reference's metadata

1.11.2 Summary

Peter J. H. et al. produced significant visionary work underlining and defining healthcare services based on the decision-making processes. The authors introduced a taxonomy framework and reviewed more than 400 publications in its scope. This work is outdated regarding the relative methods for a particular healthcare problem. Nevertheless, the value of this research lies in the terminology and classification methodology. After each subsection, the methods available at the time were highlighted. The authors underline five solution domains: computer simulation, Markov processes, math programming, queueing theory, and heuristics. The preset literature review has significant value in establishing a taxonomy structure and describing the existing healthcare problems from the decision-making perspective.

1.11.3 Notes

- ORchestra - literature database introduced and maintained by the Center for Healthcare Oprations Improvement and Research (CHOIR);
- Definitions of Strategic Planning, Tactical Planning, Operational Planning, Offline OP, and Online OP;
- Healthcare services definitions;
- Data Envelopment Analysis (DEA) and Stichastic Frontier Analysis (SFA) (91);
- Search terms in the Appendix B;

- Business Source Elit (135), PubMed (346), and Scopus (372) did not add much literature materials;

- Definitions of the healthcare services in the each level of the decision-making hirarchi;

- Look into Markov processes;

- Valuable Appendices at the end of the paper;

1.11.4 Reading

Abstract: The authors provide a taxonomy analysis and review of the papers in Operations Research amd Management Science for the Healthcare. The review descrives the existing techniques (prior 2012) for making a planning and controll desicions.

Objectives: Aim to guide healthcare proffectionals in the field of OR/ MS.

Page 1: The first page provides a basic introduction into the field of effective resource management. The definition of the Operations Research and Management Science as a cross field of various natural and cosial scinces.

Page 2: The authours touched on the application of the OR/MS and also introduces the CHOIR and ORchestra database. The paper contains sections dedicated taxomony, OR/ MS practicies in healthcare, and the literature review. The authors layed out the deeper explanation of the taxonomy and explaned the architecture of the healthcare services by level of desicion making (strategic, tactical, opearional-offline, operational-online).

Page 3: More about selected taxonomy approach. Here are presented definitions for each of the desicion-making levels.

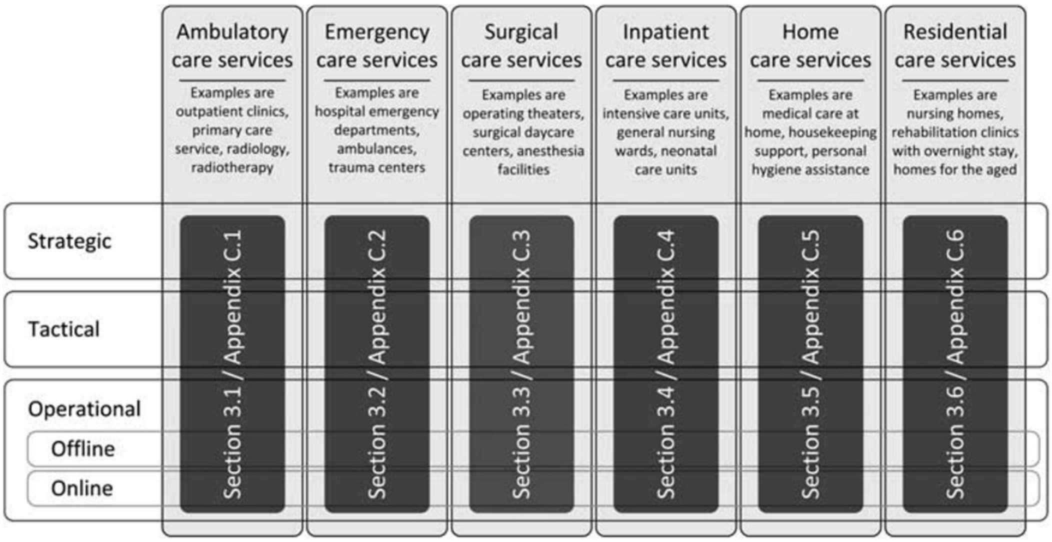


Figure 1.45: Visualisation of the OR/MS structure in healthcare [10].

Page 4: The interconnections between the desicion-making levels are outlined on this page. Then the definisions for multiple healthcare services are presented.

Page 5: The research questions, methodology, and the methods were described in more details. The authors ephacise the need to focus on decision-making aspects of healthcare.

Step 1: Identify search terms from reviews, books and MeSH
Step 2: Search the OR/MS subject category in WoS with the search terms
Step 3: Select a base set: the 10 most-cited articles relevant for our review
Step 4: Perform a backward and forward search on the base set articles
Step 5: Search relevant articles from HCMS

Figure 1.46: The search method applied for each healthcare service in [10].

Page 6: More healthcare services' definitions. Regional coverage = Ambulance care + location + demand (methods: si,ulation, heuristics, has lit. review). (Service mix) = organisation decision + ambulatory service (methods: no papers found). Case mix = facility + patient group (methods: not much but simulation, and math programming). Panel size = demand and capacity balance (methods: simulation, queueing theory). Capacity dimansioning = consultaiont room + staff + consultation time capacity + equipment + waiting room (methods: simulation, Markov processes, math programming, queueing theory, lit. review)...

Page 7: ...Facility layout = reception area + waiting area + conculstaion room (methods: no articles, but there is a book on heuristics). Patient routing = flow + optimization(methods: simulation, queueing theory). Capacity allocation = resource group + patient group + time subdivision (simulation, math models, lit. review). Temporary capacity change = equilibrium between time access and utilisation (methods: simulation). Access policy = healthcare accessability + appointment type (walk-in, same-day, standart schedule; methods: simulation, heuristic, Markov processes, queueing theory)...

Page 8: ... Adminssion control = waiting list + rules of access (methods: simulation, heuristics, Markov processes, math. programming). Appointment scheduling: Number of patients per consultation, Patient overbooking, Length of the appointment intercal, Number of patients per appointment slot, Sequence of appointment, Queue discipline in the waiting room, Anticipation for inscheduled patients (methods: simulation, heuristics, Markov processes, math programming, queueing theory, lit. review)...

Page 9: ... Staff-shift scheduling = staff + timetable + demand-capacity balance (methods: simulation, math programming, lit. review). — Offline operational planning —: patient-to-appointment assignment = appointment time + facility + patient, examples are: Signle appointment, Combination appointment, Appointment series (methods: heuristics, Markov processes, math programming). Staff-to-shift assignment = medical personnel + timetable (methods: meth programming, lit. review). — Online operational planning — Dynamic Patient (re)assignment = uncertainties + patient + rescheduling (methods: simulation, Markov processes, math programming). Staff rescheduling = demand fluctuations + staff absenteeism (no paper found).

Page 10: This page underlines the Emergency care services particularly by their regional coverage. This includes the location of the emergency care centers and the available trasportation in ambulance to reach far regions (methods: simulation, heuristics, Merkov processes, mathematical programming, lit. review)...

Page 11: ... Service mix = services + emergency (methods: no papers found). Ambulance districting = area segmentation + ambulance (methods: simulation, heuristics, mathematical programming, queueing theory).Copacity dimensioning = emergency + facility capacity + minimal costs + availability (methods: simulation, heuristics, math programming, queueing theory, lit. review)...

Page 12: ...Facility layout as the name suggests (methods: simulation, heuristic, lit. review). — Tactical planning — Patient routing = emergency + patient flow + desicion-making (methods: simulation, queueing theory, lit. review). Admission control = priorities + demand-capacity balabce (methods: simulation, queueing theory). Staff-shift scheduling = demand-capacity balance + medical personnel (methods: simulation, heuristics, queueing theory, lit. review)...

Page 13: ...— Offline Operational Planning — staff-to-shift assignment = minimise costs + personnel availability (methods: heuristics, math programming). — Online Operational Planning — ambulance dispatching = emergency + logistics + priority (methods: simulation, heuristics, math. programming, queueing theory). facility selection = logistics + priority (methods: simulation). Ambulance routing = logistics (methods: no paper found). Ambulance relocation = logistics + desicion-making (methods: simulation, Markov processes, math programming, lit. rev)...

Page 14: ... Treatemtn planning and prioritization = prescriptions + urgency + medical resource availability, also facility layout, patient routing, and admission control (methods: simulation). Staff rescheduling = capacity flexibility + staff availability (methods: simulation, math. programming). — SURGICAL CARE SERVICES - Strategic Planning — Regional coverage = facility prioritisation (methods: simulation, math programming). Service mix = service prioritisation + demand (methods: no papers found). Case mix = patient groups + financial status balance (methods: simulation, math programming, lit. review)...

Page 15: ...Capacity dimensioning = operating rooms + operating time capacity + presurgical rooms + recovery wards + ambulatory surgical ward + equipment

+ staff (methods: simulation, heuristics, math programming, queueing theory, lit. review). facility layout = demand-capacity balance + location (methods: simulation, heuristics + lit. review).— Tactical Planning — Patient routing = pre-, peri-, post-operative rooms (methods: simulation, heuristics, math. programming, lit. review). Capacity allocation = patient group identification + time subdivision + block scheduling , and also strategic level of patients groups (methods: simulation, heuristics, Markov processes, math programming, lit. review)...

Page 16: ... Temporary capacity change = flexible capacity (methods: simulation, math programming, lit. review). Unused calaptity (re)location = flexible scheduling (simulation, heuristics, Markov processes, lit. review). Admission control = balancing patient services, resource utilsation, and staff satisfaction (methods: simulation, markov processes, math programmin, lit. review)...

Page 17: ... Staff-shift scheduling = capacity-demand balancing (methods: heuristic, meth programming, lit. review). — Offline operational planning — Staff-to-shift assignment = dinamic scheduling (methods: no papers found). Surgical case scheduling = preoperative stage duration + surgical procedure duration + switching time + postsurgical recovery duration + emergency patient interruption + staff availability + starting time of a surgery (methods: simulation, heuristics, Markov processes, math programming, queuering theory, lit. review)...

Page 18: ... — Online operational planning — Emeregency case scheduling = prioritisation + rescheduling + flexible scheduling (methods: math programming, lit. review). Surgical case rescheduling = rescheduling + flexible scheduling (methods: math programming, lit. review). Staff rescheduling = ?? (methods: no paper found). — INPATIENT CARE SERVICES - Strategic planning — regional coverage = facilities' number + type + location (methods: simulation, math programming, queueing theory)...

Page 19: ... Service mix = hospital facilities (methods: no papers found). Case mix = capacities for patients (methods: simulations, heuristics). Case unit partitioning = healthcare department segmentation (methids: simulation, meth programming, queueing theory)...

Page 19: ...Capacity dimensioning = beds + euqipment + staff (methods: simulation, heuristics, Markov processes, math programming, queueing theory, lit. review)...

Page 20: ... Facility layout = flexible/ modular space (methods: si,ulation, heuristic, math programming). — Tactical Planning — Bed reallocation = prioritisation of the capacity (methods: simulation, heuristics, math programming, queueing theory). Temporary bed copacity change = trends/ season prediction (methods: simulation, heuristics, queueing theory). Admission control = time management, which can be static or dynamic, also static/ dynamic bed reservation, overflow rules, influence surgical schedule (methods: simulation, heuristics, Markov processes, math programming, queueing theory)...

Page 21: ... Staff-shift scheduling = demand prediction + capacity allocation + inpatient (methods: simulation, heuristics, math programming, queuering theory, lit. review). — Offline Operational Planning — Admission scheduling = rules for patient time and service allocation (math programming). Patient-to-bed assignment = patient preferences + availability (methods: heuristics, math programming). Discharge planning = discharge rules and regulations aimed to reduce ”bed blocking” (methods: simulation, queueing theory, lit. review)...

Page 22: ... Staff-to-shift assignment = several weeks + shift assingment (methods: heuristics, math programming, lit. review). — Online operational planning — Elective admission rescheduling = desicion macking + flexible scheduling (methods: simulation, heuristics, queueing theory). (Acure admission handling) = admision rules + desicion-macking (methods: simulation, queueing theory). Staff schedulign = personnel availabitili, also consider float, part-time, on-call, absenteesim, and voluntary shifts (methods: simulation, math programming, lit. review). Nurse-to-patient assignment = allocating patient care + workload balance (methods: simulation, heuristics, math programming). Transfer scheduling = staff choriography (methods: Markov processes).

Page 23: — HOME CARE SERVICES - Strategic Planning — Placement policy = patient groups + elligability rules (methods: heuristics, Markov processes, math programming, lit. review). Reglonal coverage = care capacity + location (methods: lit. review). Service mix = service group selection (methods: lit. review). Case mix = service selection + demand (methods: lit. review). Panel size = demand forcasting + planning (methods: math programming)...

Page 24: ... Districting = logistics + demand evaluation (methods: heuristics, lit. review). Capacity dimensioning = resource availability such as staff, equipment, fleet vehicles + budget planning + bottlenetck management (methods: simulation, Markov processes, queueing, lit. review). — Tactical planning — Capacity allocation = considering areas and patient groups + workload balance (methods: heuristics, math programming, queueing theory, lit. review). Admission control = demand-supply balance + demand evaluation (methods: Markov processes, math programming, queueing theory)...

Page 25: ... Staff-shift scheduling = uncertainties + patient preferences + personnel availability (methods: heuristics, lit. review). — Offline Operational Planning — Assessment and intake = patient elligability (methods: heuristics, Markov ptocesses, math programming, lit. review). Staff-to-shift assingment = personnel assignemnt for several weeks ahead (methods: heuristics, math programming, lit. review)...

Page 26: ... Visit scheduling = short-term plan + staff-to-visit assignment + route creation (methods: heuristics, Markov processes, mathematical programming, lit. review). — Online Operational Planning — Visit reschediling = emergency perception + flex scheduling (methods: heuristics, mathematical programming). Residential case services = governments + rules and regulations. — Strategic Planning — Placement policy = rules and regulations + capacity planning + patient evaluation (methods: simulation, heuristics, Markov processes, queueing theory)...

Page 27: ... Regional coverage = logistics + patient evaluation + capacity planning (methods: math programming, lit. review). Case mix = patient classification, for instance rehabilitation short-stay or a geriatric long-stay (methods: heuristics). Capacity dimenshioning = facilities + equipment + personnel (methods: conputer simulation, Markov processes, queueing theory).

Page 28: — Tactical Planning — Admission control = rules and guidance + priority (methods: simulation, math programming). — Offline Operational Planning — Treatment scheduling = weeks in advances + patient evaluation + demand evaluation (methods: math programming).

Conclusion: The authors dedicated this research to healthcare proffesionals to increase their awairness and to improve the healthcare scheduling practicies. In the review the taxonomy framework was introduces and the literature analysis was carried on followith the structure of the framework. The authors claimed that the desicion-making in healthcare has promising results now and further potential for the future research.

1.12 SR03US23

1.12.1 Meta

Title: Applications of Artificial Intelligence in the Radiology Roundtrip: Process Streamlining, Workflow Optimization, and Beyond

Rank	Grasp	Grade	Type	Outcome	Domain	COV19	CoI	DB
1	85%	C	A	P	B	Yes	Yes	No

Table 1.12: Reference's metadata

1.12.2 Summary

Kevin Pierre et al. [11] proposed a general overview of existing AI applications in radiology. The review highlights many examples; however, only two examples are somehow related to medical resource scheduling: radiology screening scheduling and image prioritisation for more efficient reporting and diagnostic time. The structure of the study can be improved. The authors praise the benefits of the AI approaches and do not mention the cons of the implemented solutions or possible ethical issues of exposing electronic medical data to machine learning algorithms. The work was conducted in collaboration with Nuance Communications Inc. and GE Healthcare, and has acted as a speaker or consultant for these entities.

1.12.3 Notes

- Picture Archiving and Communication System (PACS);
- Clinical Decision Support (CDS);
- Appropriate Use Critaria (AUC)-CDS model;

1.12.4 Reading

Abstract: The authors outline benefits of using AI in the radiology which are beyond diagnostic practicies.

Objectives:

Page 1: The emphasis in the introductio is on the ML approaches to ”learn” in comparison with the traditional computational methods.

Page 2: The standart approaches to solve radiology issues some times even does not consider need of a patient, when data driven methods like Natural Language Processing (NLP) has potential to work from data and therefore automatically be more practial in the real hospitals, not just in simulations.

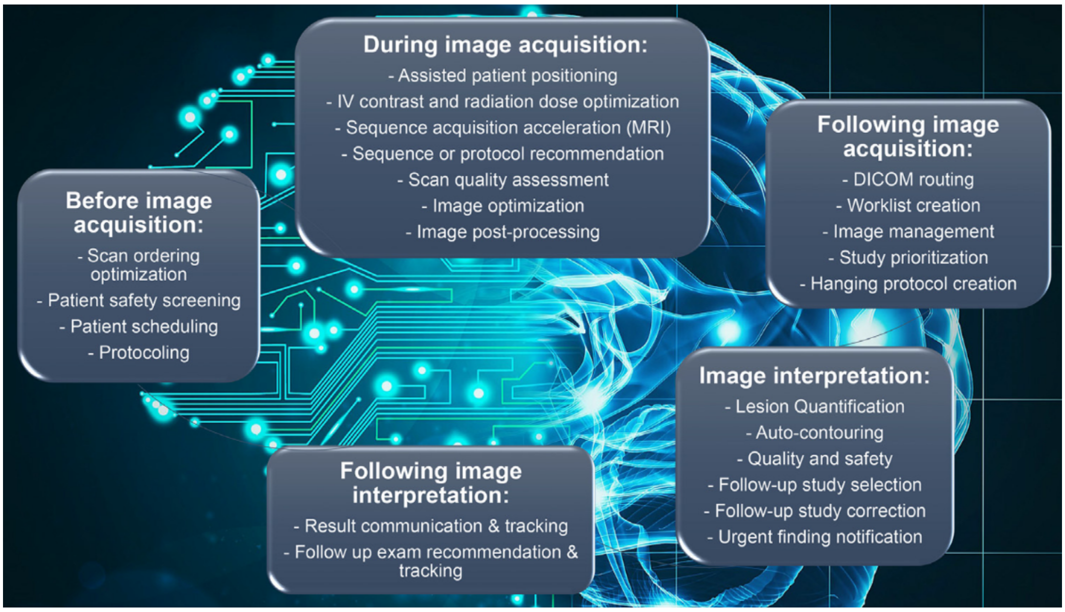


Figure 1.47: Application of AI in radiology from [11].

Page 3: This page provides some information on how imaging diagnostics in radiology works, possible analysis methods, and related little to the methods themself.

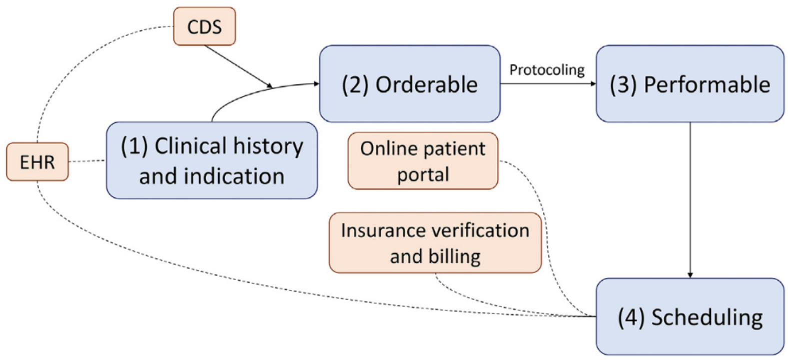


Figure 2 Potential applications of AI to optimize imaging examination scheduling. Once an order has been placed (orderable), the main steps in this process are amenable to AI assisted streamlining and automation, including protocoling or selection of a "performable" that will provide the required information for scheduling. The process can be informed and enhanced by information in the patient's EHR and CDS, potentially also supported using ML and NLP. For example, the software may assess whether a creatinine level was obtained and whether it was within normal limits when required prior to an examination requiring intravenous contrast administration. Once such a system is in place, other optimizations using AI will also be possible, such as coordination with insurance to ensure billing compliance. Eventually, one may even envisage a system where the software can perform scheduling coordination and reconciliation with a patient's availability and preferences through an interactive online patient portal. EHR: Electronic health record. CDS: Clinical decision support.

Figure 1.48: Structure of a potential AI application in Radiology from [11].

Page 4: In the first part of this page, the implementation an AI system was descriped. This sistem will flag inappropriate screenings or tests for patients due to alergies or/ and implants incompatible with the screening equipment. On the rest of the page, the protocoling of radiology procedures was describer. The radiologist may spend unnesessaty working hours on protocoling the radiology results wich is usually follow standart set of rules. There is known applications of AI where the NLP can relativelly accuarate and consistant make protocols for radiology screening.

Page 5: Efficient scheduling is an important aspect of the radiology patient flow. There is a place for an AI implementation. The positioning of an equipment during the scanning can be an issue. There are commersial AI systems which can solve this issue lieaing to enhanced screening result and lesser radiation exposion for patients. In addition, another ML model can adjust an optimal IV contrast radiation dosage for smaller exposior and sufficient screening outcome. Going even further, specialised Convolutionary Neural Networks can denose underexposed images minimising the chance of repetative scanning.

Page 6: The ML models can optimise workload by establishing the priorities for screens in the queue. Furthermore, the segmentation of the radiology images help identify the diagnosis for patients.

Page 7: The AI tools system are also used to improve reporting, also workflow by notifying specialists about some required work to finish on rediolofy images. Other applications of the AI solutions contain educational purposes like providing a feedback on the quality of a radiological report.

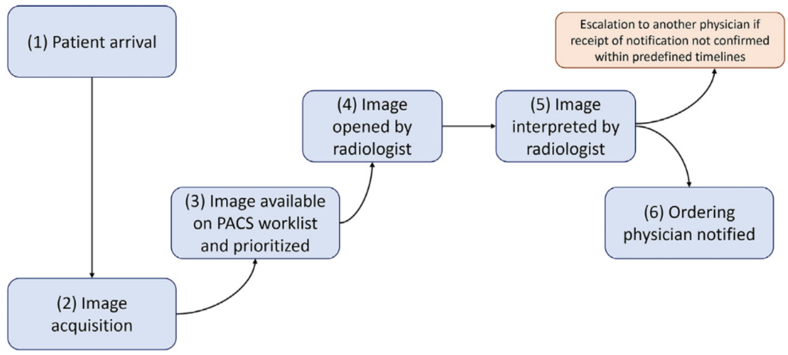


Figure 3 AI worklist prioritization and urgent finding notification. There is also potential for escalation to another physician or the department chief if the receipt of notification is not confirmed within a predetermined acceptable time interval based on the level of urgency of the finding.

Figure 1.49: AI worklist prioritisation from [11].

Page 8: Quality assurance and Patient Safety: repeats the previuse applications. Billing and Comliance: by increasing radiology care efficiency thus reducing its costs. Miscellaneous Applications: lists other less investigated applications of AI in radiology.

Conclusion: Standart computational methods are good but AI approaches are better.

1.13 SR01CN19

1.13.1 Meta

Title: Operating room planning and surgical case scheduling: a review of literature

Rank	Grasp	Grade	Type	Outcome	Domain	COV19	CoI	DB
5	95%	B	A	P	S	No	Yes	No

Table 1.13: Reference's metadata

1.13.2 Summary

Shuwan Zhu et al. [12] provided a literature review with classification considering operating room planning and scheduling. From the construction point of view, the paper is very similar to [10]. For instance, both studies concentrate on the scheduling problems, not the solutions, but with some noteworthy differences. First, the study demonstrates quantitative literature analysis, absent from [10]. Second, the paper's structure is looser, and finally, the terms and definitions are more up-to-date. On the other hand, the authors of [10] proposed more concrete and fundamental explanations for terms in healthcare planning and scheduling. Ultimately, this paper represents a valuable asset for newcomers in the field regarding terminology and general trends.

1.13.3 Notes

- PubMed, Web and Science, IEEE, Springer, and Inspec;

- Terms definitions;

1.13.4 Reading

Abstract: It is a comprehantice review of studies in the operating room planning and surgery case scheduling. The interested aspects of the review are: decision levels, scheduling strategy, patient characteristics, problem definition, uncertainty, and solution approaches. The quantitative analysis of the existing publications shows that the most interested planners are build with math models and heuristics.

Objectives: ??

Page 1: Operating theatres are a focal point in improving medical care efficiency for most hospitals.

Page 2: The number of literature reviews show that the operating room planning is a field of high scientific interest. The authors overviewd 315 studies, where more then half were published after 2010.

	1950–1999	2000–2009	2010-Present	Total
Journal	35	83	149	267
Proceedings	3	12	13	28
Working paper	1	4	7	12
Other	5	1	2	8
Total	44	100	171	315

Figure 1.50: Distribution of reviewved works by type and year of publication [12].

Page 3: The literature review convers six aspects of the operational room planning: desicion levels, scheduling strategies, patient characteristics, problem features, math models, solutions and methods. The decision classification includes strategic, tactical, and operational levels of decision-macking. To strategic level problem can be related: capacity planning problem, capacity allocation problem, and case-mix problem.

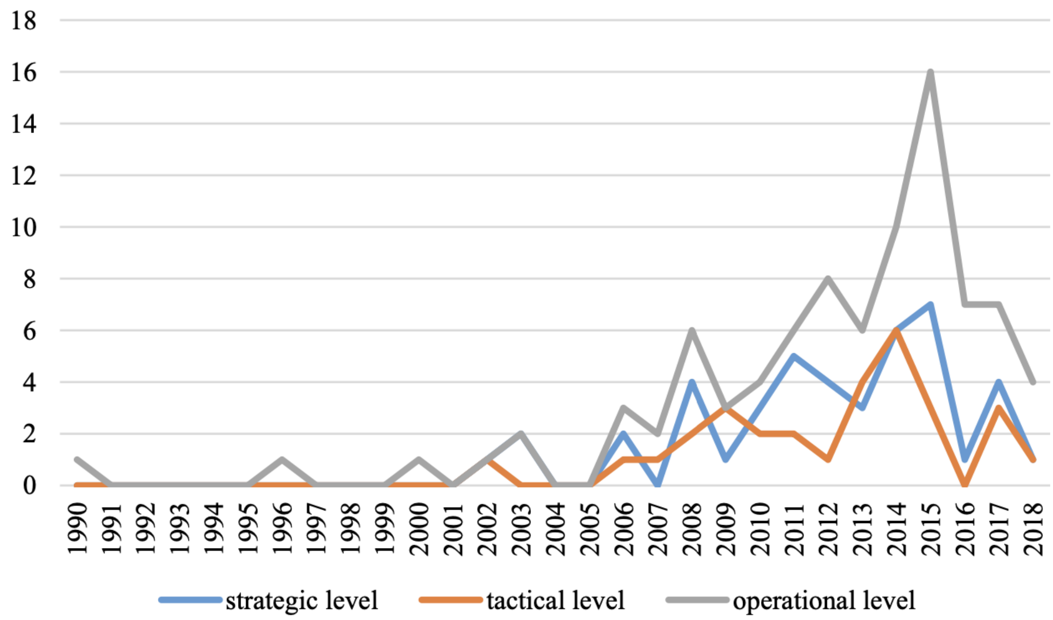


Figure 1.51: Publication trends classified by desicion levels in [12].

Page 4: Capacity planning = resouces + demand-capacity balance.

Page 5: Capacity allocation = long-term horizon + operating room + specialities. Case-mix problem (CMP) = long-term horizon + resource + time blocks.

Page 6: Tactical level = mediom-size horizon (month, quartal) + cyclic schedule + resouce allocation + specific times / time blocks / flexible time blocks. (reflection: the tactical level gets so far more attention then the strategic level description).

Page 7: Operating level (Surgeon Scheduling Problem (SSP), Patient Scheduling Problem) = advance scheduling and allocation. Advance scheduling (intervention assignment, surgery case assignment) = surgery case + date of operation + operation room.

Page 8: Allocation scheduling (intervention schediling, surgical case scheduling) = waiting list + day plan + possible pre-assignments.

Page 9: Some studies develop an integration of advance scheduling and allocation scheduling together, and even consider downstream capacities. (reflaction: it is the sence of practical model, isn't it?). Scheduling strategies involve: block strategy, open strategy, and modified block strategies.

Page 10: Block scheduling strategies = fixed time and/or fixed patient group and/or fixed resouces which are considered in blocks.

Page 11: Open scheduling strategy = open time slots + FIFO (FCFS). The authors of this review criticise the open scheduling strategy due to low utilisation of the medical resources and often unstructured workflow for surgeons.

Page 12: Modified block scheduling strategy = combination of block and open scheduling strategies. A comment from the authors - it is harder to manage, and the there are ongoing research in the direction of modified block scheduling strategy. There are two segments of patients: elective or non-elective patients, and inpatients or outpatients.

Page 13: Inpatients and outpatients: list of related publications and no new information.

Page 14: Elective and non-elective patients: elective patients can be conventional (= inpatiets) or ambulatory (= outpatients). Non-elective patients' subclasses are emergent and urgent (reflection: sometimes could be semi-urgent cases). Most of the research focuses on the elective patients, the patients which are predominant in hospitals. Another important factor, uncertainty considered for more practical scheduling models.

Page 15: Uncertainty is a significant aspect for the medical resource scheduling. Most of the studies ignore it, and some try to conquer unsertanties using methods with stohastic nature.

Page 16:

Publication	Duration	Objective	Method	Type of analysis	Factors
Rath et al. (2017)	$[\overline{d_i} - \widehat{d_i}, \overline{d_i} + \widehat{d_i}]$	$\sum w_i c_i$	A data-driven robust optimization	Approximate	Anesthesiologists; ORs
Guda et al. (2016)	$d \sim N(\mu, \sigma^2)$	$\min \left[\sum_{j+1}^{n} \left[\begin{array}{l} c_w \left(S_j^\pi - A_j^\pi \right)^+ \\ + c_I \left(A_j^\pi - S_{j-1}^\pi - Z_{\pi_{j-1}} \right)^+ \end{array} \right] \right]$	Shortest-Variance-First (SVF) rule	Approximate	Surgeons; ORs
Addis et al. (2016)	$d \sim N(\overline{t_i}, {\sigma_i}^2)$	$\min \sum_{i \in I} \left\{ \begin{array}{l} \sum_{j \in J} \sum_{k \in K} \left[d_{jk} + (w_i + d_{jk} - l_i)^+ \right] \\ u_i x_{ij}^k + \left[(w_i + D + 1) + (w_i + D + 1 - l_i)^+ \right] \\ u_i \left(1 - \sum_{j \in J} \sum_{k \in K} x_{ij}^k \right) \end{array} \right\}$	Scheduling-rescheduling framework	Approximate	Total waiting time and tardiness of patients
Dios et al. (2015)	$\ln p \sim N(\mu, \sigma^2)$	$\sum_{p \in P} w_p \sum_{t \in T} \sum_{r \in R} \frac{Z_{prt}}{t}$	A decision support system	Exact and approximate	Material and human resources
Silva et al. (2015)	$d \sim U(1, 11)$	$C_{\max}; \sum_{s \in S} \sum_{r \in R_s} \sum_{t \in T_s} d_s y_{st}^r$	Relax-and-fix heuristic	Approximate	Human resources
Astaraky and Patrick (2015)	$\ln p \sim N(\mu, \sigma^2)$	$\left(\sum_{p=1}^{P} r_p \varphi_p(i) \right)$	Policy iteration algorithm; dynamic programming methodology	Approximate	The cost of overtime in the OR; cost of exceeding the bed capacity

Figure 1.52: Some objectives from literature by [12], part I.

Page 17:

Publication	Duration	Objective	Method	Type of analysis	Factors
Day et al. (2012)	$\{0, 1, 2, \ldots, 100\}$	$\left(\sum_{i \in D} \sum_{k \in K_i} \left[(v_i + \pi_i) \left(u_{ik}^p + u_{ik}^s \right) - h_i \sigma_{ik}^+ \right] x_k - c \sum_{j \in B} r_j \right)$	Column generation; Simulation; Benchmark	Approximate	Surgeons; ORs; shared block time
Shylo and Prokopyev (2012)	$d \sim N(\mu, \sigma^2)$	$\min \left\{ \sum_{b \in b \backslash b_m} \mathrm{E} \left[\left(l(b) - \sum_{s \in S} d_s x_{s,b} \right)^+ \right] \right\}$	An optimization framework; Theoretical properties	Approximate	OR capacity; surgeons; unique piece of equipment; overtime of block
Batun et al. (2011)	Scenarios	$\sum w_i c_i$	Structural properties	Approximate	ORs; surgeons
Denton et al. (2010)	$\underline{d_i} \leq \delta_{ij} \leq \overline{d_i}$	$\min \sum_{j=1}^{m} (c^f x_j + c^v o_j)$	Heuristic	Approximate	ORs; surgeons; nurses

Figure 1.53: Some objectives from literature by [12], part II.

Page 18:

Publication	Objective	Method	Type of analysis	Factors
Roshanaei et al. (2017b)	$\min \sum Gu + \sum kx$	Logic-based Benders decomposition (LBBD)approaches	Exact	ORs
Guido and Conforti (2017)	opt $f(x) = [f_1(x), f_2(x), f_3(x), f_4(x), f_5(x)]$	Hybrid genetic solution approach	Exact and meta-heuristic	Surgical specialty; surgical teams
Riise et al. (2016)	$\min \sum_f \alpha_f O^f$	Integration method and sequential method	Exact	Surgeons; ORs; recovery units
Doulabi et al. (2016a)	$C_{\max}; \sum_{j \in J} B_j x_j$	A branch-and-price-and-cut algorithm; dominance rules; A fast infeasibility-detection algorithm	Exact	Surgeons; ORs; deadline of surgery
Castro and Marques (2015)	$C_{\max}; \sum_{h \in H} \sum_{d \in D} O^h_{h,d}$	Decomposition algorithm	Approximate	Surgeons; specialty; ORs
Marques et al. (2015)	Maximize the number of surgeries scheduled	A weighted Chebyshev distance to a reference point	Approximate	ORs; surgery priority level; specialty
Vijayakumar et al. (2013)	$\sum_{pod} y_{pod} I_{pd}$	A heuristic based on the first fit decreasing algorithm	Approximate	Resource availability; case priorities and variation in surgery times
Meskens et al. (2013)	$C_{\max}; \min \begin{bmatrix} \sum_{o=1}^{O} \sum_{r=1}^{R} \sum_{t \geq T_{\text{sup}}}^{T} OTR(o,t,r) \\ \sum_{o=1}^{O} \sum_{b=1}^{B} \sum_{t \geq T_{\text{sup}}}^{T} OTB(o,t,b) \end{bmatrix}$	A generic model	Approximate	Surgeons; nurses; anesthetists
Creemers et al. (2012)	$\min \sum_{y=1}^{Y} w_y z_y^{\max}$	Step-wise heuristic	Approximate	Patient waiting time
Beliën and Demeulemeester (2008)	$\min \sum_{i \in I} \pi_i d_{ik}$	Branch-and-price algorithm	Exact	Nurse; surgeons; ORs

Figure 1.54: Some objectives from literature by [12], part III.

Page 19: This page starts with list of papers categorised by type of uncertainty. Then the duration uncertainty is explained as ”deviations between the actual and planned durations of relecant activities during the surgical process”.

Page 20: The modeling of uncertainty is split into to dirations: using Monte Carlo simulation, or using random probability distribution (lognormal, gamma, and normal).

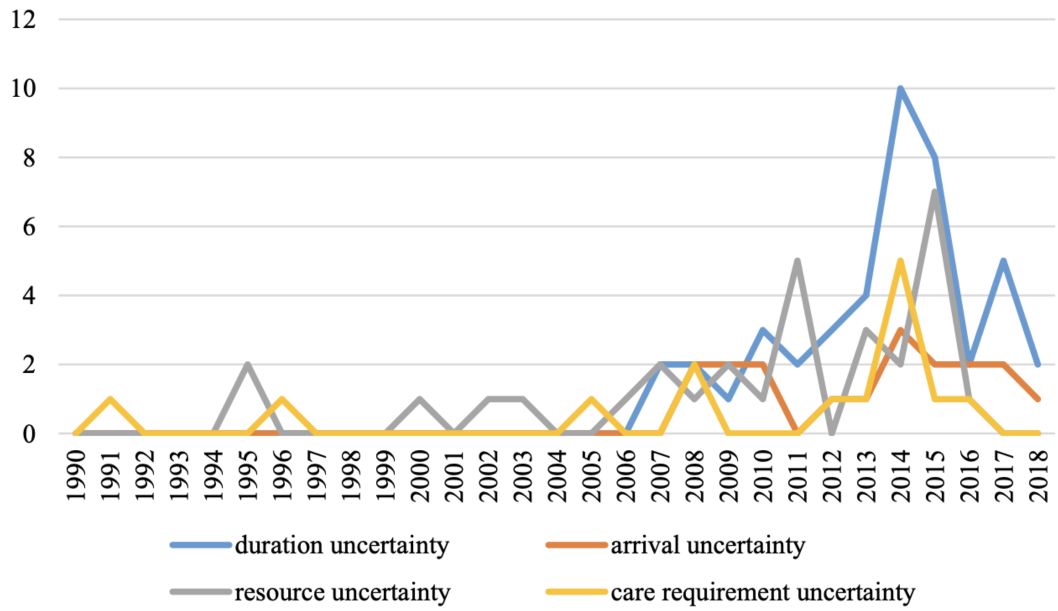


Figure 1.55: Trends in publications with uncertainties over the years from [12]

Page 21: Arrival uncertainty: not much new, sturied with simulation techniques to find a better solution to reduce arrival uncertainty factor. Resource uncertainty: unexpected equipment breack down, supply shortage, etc. Care requirement uncertainty: the other objectives which can pop-up on the way (reflaction: not clear explanation).

Page 22 (Objective functions): Certain requirement: infection cleaning and the discussion ergarding this in the reviewed publications. In addition, there could be patient specific requirements.

Page 23 (Objective functions): ... some authors design models which take into account three surgery priority levels and also human resources such as surgeons and nurses. Next is a description of multi-stage scheduling approache implemented in some of the studies. First - assign resource to operation room and caregivers; second - define the start time for the surgery.

Page 24 (Math models): Surgery planning and scheduling problem was translated into bin-packing, flow-shop, stochastic, and multi-critaria model. Bin-packing model: ORs = bins, surgery cases = items to be packed. There are on- and off-line bin-packing models.

Page 25 (Math models): Flow-shop model: described as NP-hard problem and then the relevant studies were presented. Stochastic model: adds uncertainties into idealised models. Multi-criteria model: fewver works explisitly use multi-criteria models.

Page 26 (Solutions and methods): Exact algorithm: always optimal, small-scale problem, examples: column generation, dynamic programming, branch and cut, branch and bound, and branch-and-price.

Pages 27-29 (Solutions and methods): These pages outline and show examples of the exact algorithm implementation in the reviewed papers. (reflaction: the algorithms themselves are not explained).

Page 30 (Solutions and methods): Heuristics are divided into six categories: based on exact methods, constructive, improvement, meta-heuristics, linear programming (LP) based, and dispatching-rule based.

Pages 31-34 (Solutions and methods): Tables with studies classified to different heuristic methods.

Pages 35-36 (Solutions and methods): List of the literature with solutions.

Page 37 (Solutions and methods): Simulations: provide evaluation of the solution models for broader spectrum of cases. In sume publications, simulation approaches are used as primary solution model. The authors separate Monte Carlo simulation, Dicrete-event simulation ad others.

Page 38 (Solutions and methods): Markov decision process (MDP): is practical for veriaty of optimisational approaches that focuse on on dynamic programming and reinforcement learning.

Pages 38-39 (Conclusions): The operating room scheduling is a complex task. The authors conducted a literature review and classified the studies in multiple sections and subsections. Majority of the research dedicated to short-term horizons. The unsertainties are often ingnored which is not practical considering the unpredicitble nature of the operating rooms scheduling problem.

1.14 SR02CN23

1.14.1 Meta

Title: A Literature Review of Service Capacity Planning for Medical Technology Department

Rank	Grasp	Grade	Type	Outcome	Domain	COV19	CoI	DB
2	95%	D	A	P	B	No	??	No

Table 1.14: Reference's metadata

1.14.2 Summary

Hongying Fei and Yiming Kang[13] produced a general overview of the existing literature regarding service capacity planning for the medical technology department. The review needs a more substantial structure. The authors categorised the literature by patient type, attendance, and uncertainty. The summaries of the reviewed literature are presented. The conducted study has little value for newcomers who want to gain a general understanding of existing research.

1.14.3 Notes

- Projection method?

1.14.4 Reading

Abstract: The medical services play crusial role in the quality of healthcare system. The current review overviews, structures, and summarises latest research in the topic of service capacity planning.

Objectives: To identify and structure the most recent studies in the field of healthcare service capacity planning.

Page 1 (Introduction): There is more demand for healthcare services then capacity. The optimisation of healthcare capacities requires an efficient management of the expancive and valuable resources (surgeons, nurses, and modern medical equipment). Two stages form a healthcare service capacity planning: resource allocation and capacity design. Medical Technology Department is a significant part of healthcare. The authors review and analyse the existing literature and then draw conclusions and suggestions from the conducted review.

Page 2 (Essentials for MT department): The most valuable aspects of MT department are: patient beds, medical personnel, operating rooms, and the medical equipment. The demand on MT services is drastically increased.

Page 3 (Service Capacity Planning): Demand. The demand is an important factor in evaluation healthcare needs. Here some discussion and possible demand estimation methods from the literature are presented.

Page 4 (Service Capacity Planning): Patient Attendance. List of papers. Patient demand and no-show prediction. Unsertainty. Uncertain Service Time. Stochastic models for patients waiting time prediction and uncertain healthcare service duration.

Page 5 (MT Department Service Planning): List of variouse applications of compuational methods in Medical Technology Department. The applications not always were related to the scheduling.

Pages 5-6 (Conclusions): The most common direction of research involves outpatient appointments, inpatient beds, and operating rooms. Then authors repeating the statements from the body of the paper. The last pharagraph highlights the importance of service scheduling in medical technology department. (reflaction: the conclusion is unclear.)

1.15 SR04US22

1.15.1 Meta

Title: Stochastic optimization approaches for elective surgery scheduling with downstream capacity constraints: Models, challenges, and opportunities

Rank	Grasp	Grade	Type	Outcome	Domain	COV19	CoI	DB
5	84%	A+	A	P	B	Yes	??	Yes

Table 1.15: Reference's metadata

1.15.2 SR04US22

Karmel S. Shehadeh and Rema Padma [14] propose a complex literature review on stochastic optimisation approaches for elective surgery scheduling with downstream capacities. The review focuses on three solution approaches from January 2010 to November 2020: Stochastic Optimisation (SO), Robust Optimisation (RO), and Distributionally Robust Optimisation. The importance of the research is stated, and the statements were supported with statistical data about the value of the operating theatres and the downstream capacities in hospitals. In the body of the paper, the authors describe individual parts of elective surgery scheduling, explain interconnections among constraints, and discuss the mathematical interpretations of the SO, RO, and DRO solutions. The examples of the solutions in other studies were demonstrated and discussed. The language in the research is addressed to advanced readers with sometimes excessive terminology. The paper proposed multiple suggestions on how it is possible to improve existing solutions and outlined further research areas. In conclusion, this literature review presents high-quality qualitative research with practical guidelines and in-depth knowledge of the researched field.

1.15.3 Notes

- Starts with quotations;
- OR 40%-70% revenue (refs);
- OR 20%-40% operating costs (refs);

- SICU 15%-40% hospital costs (refs);
- Agency for Healthcare Research and Quality (AHRQ);
- 17.2 million hospital visits in 2014;
- Patients require surgery: 60%-70%;
- Specific way of useing ”multi-modal”;
- Healthcare in formation technologies (HIT);
- SO, RO, and DRO (Jan2010-Nov2020);
- Cost of cancelled case \$1700-\$2000, Argo et al.(2009);
- 15% of cancellations lack of recovery beds;
- Survival rate SICU = noSICU x 6;
- Data of the Erasmus University Medical Center;
- Real-time location system (RTLS);
- Advanced technical, specialised language;
- Goh, J., Sim, M., 2010. Distributionally robust optimization and its tractable approximations. Oper. Res. 58 (4-part-1), 902–917;
- Written with the reader in mind;
- Waht is Mig-M?
- Contains valuable references;
- E-HOSPITAL workbench;

1.15.4 Reading

Abstract: The flow of surgery operation with downstream capacity was explained. The authors conducted a review on existing solutions with focus on Stochastic Optimisation. The description of the processe of solving elective surgery scheduling was provided together with the suggestions for creating ”tractable, implementable, and data-driven” solution methods.

Objectives: Motivated by research collaboration with a large health system in Pennsylvania.

Page 1 (Quotations): *“Each of the uncertainty veils carries a secret promise for creative mathematical art.”* - Dr. Karmel S. Shehadeh (2021)

“Problems worthy of attack prove their worth by hitting back.” – Piet Hein, Grooks (1966)

Page 1 (Introduction): The authors backed the value of operating rooms by showing the numbers of the revenue it produces of amoung all hospital sources, and costs it requires in porcentile to all hospital expances. The description of OR scehduling and introduction of the three decision stages are stated next.

Page 2 (Introduction): Three levels: strategic, tactical, and operational. Operational splits further into advance and allocation scheduling. The stochastic nature of the surgery scheduling problem such as operation duration and lenght-of-stay (LOS) raise additional obsticle on the way of optimal operating room usega. The normal distribution do not fully reflect the real fluctuation of the surgery durations. Multi-modal = multi-modality = bimodal = bimodality = not unimodal = not fully known. Lack of information leads to inefficient OR utilisation. The OR scheduling with downstream capacity is a special case of ”stichastic hybrid flow shop scheduling, which is NP-hard”. There is no working framework for navigating in OR scheduling. The existing heuristic solutions are usually sub-optimal and lack the operational efficiency. The cooperation with large Pennsylvania health system and methodology description are described.

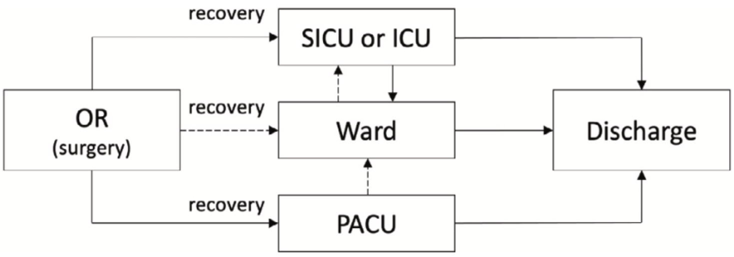


Figure 1.56: Potential patient flow in [14].

Page 3 (Introduction): This paper does not consider emergency surgeries. The focus of the review lies in on the OR scheduling with downstream capacity, any papers that go beyond this critaria re out of scope of this research. The outline of the work finalyses the introduction section.

Page 3 (Impact of uncertainty): The parameters of the uncertainties in OR scheduling will be introduced further in this section. fluctuating surgery duration: surgeon workload, surgery work-content such as surgery type, surgery sequence, priority constraints, degree of timeoverlap between surgeries (refs). The duration is often an input parameter for scheduling algorithms. Length of Stay: related to SICU (days), inpatient wards (days), and PACU (hours), and depends on surgery type, anaesthetics, patient. Surgery cancellation leads not only to financial loss, but also to worsenning the health state for patients.

Page 4 (Impact of uncertainty): . . . PACU is known as a bottleneck of the surgeries flow in hospitals. 20-hour PACU blocking caused up to $44,000 for a pediatric hospital in California (not including overtime costs, additional revenue losts from following cancellations). /underlineImpact and challenges of multimodality: most of the papers doew not consider uncertainty of the scheduling problem, most of which is due to unability to access real hospital records. According to data of the Erasmus University Medical Center the durations of the surgeries are fluctuating and not uniformally. It is impossible to know whether or not the complecations occure during the surgery operation. Therefore, papers which are not considering uncertainty are suboptimal. Opportunities for modeling uncertainty: by improving IT systems in hospitals, for example, by using RTLS systems. The EHRs are still under development and in process of addoptimng for many hospitals. There is a study on FJSS implementation inte hospital information and management system (HIMS).

CVM	Composite variable modeling
DRO	Distributionally robust optimization
DR	Distributionally robust
EHR	Electronic health record
FJSS	Flexible job shop scheduling
HIT	Healthcare information technology
i.i.d	Independent and identically distributed
IT	Information technology
LP	Linear program/programming
LOS	length-of-stay
MDROM	Multi-stage DRO model
MILP	Mixed-integer linear program/programming
ML	Machine learning
OR	Operating room
PACU	Post-anesthesia care unit
PHU	Preoperative holding unit
RO	Robust optimization
RTLS	Real-time locating systems
SAA	Sample average approximation
SASS	Single-provider appointments sequencing and scheduling
SICU	Surgical intensive care unit
Select_Assign	Surgery selection and assignment problem
Seq_Sched	Sequencing and scheduling problem
SO	Stochastic optimization
SP	Stochastic program/programming
w.p.1	with probability one

Figure 1.57: Acronyms in [14].

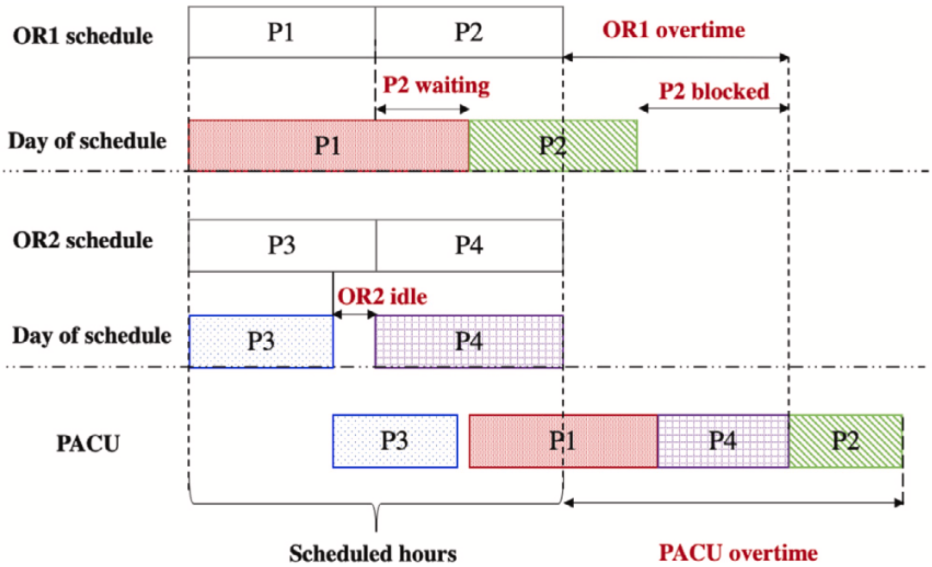


Figure 1.58: Two-OR and one-PACU patient flow from [14].

Page 5 (Stochastic optimisation): There are three diractions to handle uncertainty in the scheduling problem: stochastic programming (SP), robust optimisation (RO), and distributionally robust optimisation (DRO). The short comaprison of the three diractions will be presented in this section. SP is efficient tool until the number of variables is low, when it is a lot of variations, the problem becomes exponantialy hardert to solve. To simplify the calculations, some authors resort to Monte Carlo simulation, which reduces number of solutions it tries to render. Then the authors proposed literature on techinal details of the sample average approximation (SAA). Next the robust optimisation is explaint in math terms. DRO is presented as in-between SP and RO methods...

Rahimian and Mehrotra (2019). Let $x \in \mathcal{X} \subseteq \mathbb{R}^n$ represent the first-stage decisions, let $(\Xi, \mathcal{F})$ represents the underlying measurable space for a given space Ξ and σ-field $\mathcal{F}$ of Ξ, let $\xi : \Xi \mapsto \Omega \subseteq \mathbb{R}^d$ represents a vector of random parameters defined on a measurable space $(\Xi, \mathcal{F})$, $f(x,\xi)$: $\mathcal{X} \times \Xi \mapsto \mathbb{R}$ represents a random cost recourse function, and $g(x,\xi) : \mathcal{X} \in \Xi \mapsto \mathbb{R}^m$ represents a vector of random functions, i.e., $g(x,\cdot) := [g_1(x,\cdot), \dots, g_m(x,\cdot)]^\top$. Given this setup, Rahimian and Mehrotra (2019) define the general stochastic optimization (SO) problem as follows

$$\text{(SO)} \quad \inf_{x \in \mathcal{X}} \left\{ \mathcal{R}_{\mathbb{P}}\left[f(x,\xi)\right] \middle| \mathcal{R}_{\mathbb{P}}\left[g(x,\xi)\right] \leq 0 \right\} \tag{1}$$

where $\mathbb{P}$ is the known probability measure on $(\Xi, \mathcal{F})$, $\mathcal{R}_{\mathbb{P}} : \mathcal{Z} \mapsto \mathbb{R}$ is a componentwise real-valued functional under $\mathbb{P}$, and $\mathcal{Z}$ is a linear space of measurable functions on $(\Xi, \mathcal{F})$. As pointed out by Rahimian and Mehrotra (2019), *the functional $\mathcal{R}_{\mathbb{P}}$ accounts for quantifying the uncertainty in the outcomes of the decision, for a given fixed probability measure $\mathbb{P}$.*

Figure 1.59: Mach definition of the scheduling problem from [14], SP part I.

Classical SP extends the linear optimization framework to minimize a risk measure (often the total expected cost) associated with the optimal *here-and-now* (first-stage) and *wait-and-see* (second-stage recourse) decisions under a *known probability distribution* $\mathbb{P}$ of random parameters. Mathematically, SP is a special case of the SO problem in (1) and has the following classical forms:

$$v = \inf_{x \in \mathcal{X}} \left\{ F := \mathbb{E}_{\mathbb{P}}\left[f(x,\xi)\right] \right\} \tag{2a}$$

$$\inf_{x \in \mathcal{X}} \left\{ f(x) \middle| \mathbb{E}_{\mathbb{P}}\left[g(x,\xi)\right] \leq 0 \right\} \tag{2b}$$

Figure 1.60: Mach definition of the scheduling problem from [14], SP part II.

$$\inf_{x \in \mathcal{X}} \sup_{\xi \in \mathcal{U}} f(x, \xi) \tag{3}$$

$$\inf_{x \in \mathcal{X}} \sup_{\xi \in \mathcal{U}} \left\{ f(x, \xi) \middle| \sup_{\xi \in \mathcal{U}} g(x, \xi) \leq 0 \right\} \tag{4}$$

Figure 1.61: Mach definition of the scheduling problem from [14], RO.

$$\text{(DRO)} \quad \inf_{x \in \mathcal{X}} \sup_{\mathbb{P}_\xi \in \mathcal{P}} \left\{ \mathcal{R}_{\mathbb{P}_\xi} \left[f(x, \xi) \right] \middle| \sup_{\mathbb{P}_\xi \in \mathcal{P}} \mathcal{R}_{\mathbb{P}_\xi} \left[g(x, \xi) \right] \leq 0 \right\} \tag{5}$$

Figure 1.62: Mach definition of the scheduling problem from [14], DRO.

Page 6 (Stochastic optimisation): ... more of DRO explanation in math term.

Page 6 (Modeling elective surgery scheduling problem): The outline of the researched model of stochastic optimisational surgery scheduling with downstream capacity. Each specialty has its own block of time. Two stage planning: assign surgeries to the blockes, sequencing (allocating) start times of the surgeries. Typical performance metrics: cost of performing/ postponing surgeries, percentage of scheduled surgeries, OR idle and overtime, recovery unit utilisation, premature SICU transfer, OR blocking time, surgery cancellation and delay, OR and recovery units congestion, and clinical staff workload, and even more metrics in references. These is no knowned approach which can solve the scheduling with all this metrics combined, so researchers desided to divide and conter the problem into smaller dyjastible parts. Select_Assign: From I waiting list to B surgery blocks + downstream capacity. Performing/ delaying a surgery has a cost. Math formulation of the problem. SP approaches for Select_Assign: SP formulation with two costs and math model...

Page 7 (Modeling elective surgery scheduling problem): ... Starts with the list of studies. SP Solution Approaches and Challenges. Stochastic SP is replaces by deterministic MILP in two steps: select N samples with independent surgery duration and LOS; sample average of thses samples. Large scale SAA-MILP formulations. With bigger problem the sample size will also grow, therefore sometimes spliting problem into smaller chunks with other mathematical approaches may resolvethis issue. Symmertry. Simmetricaly good solutions also have their caviate: there are more local optima which can trap the progress of optimisational algorithms.

Page 8 (Modeling elective surgery scheduling problem): Distribution Anbinquity. The assamption of the certain duration hurts SP ability to preform well even in idealised scenarios. RO approaches for Select_Assign. The high scheduling time for small problems too. Unable to capture the uncertainty distribution. DRO approaches for Select_Assign. Removes non-realistic assumptions about disctribution of uncertainty for LOS and surgery duration. Better then RO. Succesfull applications. The idel time cost is a critical parameter in operating room scheduling (%37.45, Rocherster Medical Centre California). The patient sutisfaction is another important metric.

Page 9 (Modeling elective surgery scheduling problem): ... some more examples of implementing DRO. Opportunities: data-driven DRO are both "tractable" and "implementable". Next author describe the implementability but through ambiquity with math model...

(i) a risk-neutral OR manager may choose $\varrho(Q(x,\xi)) = \mathbb{E}_{\mathbb{P}}[Q(x,\xi)]$.
(ii) a risk-averse OR manager may choose $\varrho(Q(x,\xi)) = \mathrm{CVaR}_{1-\epsilon}(Q(x,\xi))$, i.e., the conditional value at risk (CVaR) of second-stage cost $Q(x,\xi)$ with $1-\epsilon \in (0,1)$ confidence.

Then, the DRO models impose a generic min–max DR objective in the form of (10a) and/or generic DR constraints in the form of (10b)

$$\min_{x\in\mathcal{X}}\Big(\sum_{i\in I}\sum_{b\in B\cup\{b'\}} c_{i,b}x_{i,b} + \sup_{\mathbb{P}\in\mathcal{F}} \mathbb{E}_{\mathbb{P}}[Q(x,\xi)]\Big) \tag{10a}$$

$$\sup_{\mathbb{P}\in\mathcal{F}} \varrho(Q(x,\xi)) \le \bar{\mathcal{M}} \tag{10b}$$

where $\bar{\mathcal{M}} \in \mathbb{R}$ represents a bounding threshold for the risk measure from above.

Figure 1.63: DRO Select_Assign Model from [14].

Page 10 (Modeling elective surgery scheduling problem): ... some examples from literature. Solution methods: there are easy to implement specific algorithm which require fine tuning and "hand work"; however the authors aim for more robust solution which will not require reassembling for each specific problem (Goh abd Sim, 2010). "For example, one can solve a more restricted version of the problem called affinely adjustable robust counterpart (AARC). Tractable DRO heuristics like AARC with distributional ambiguity has not been investigated for this class of problems." (reflection: decided to go with quotation, because do not exactly understand what is going on here). In addition, the authors propose combine computational efficiency of and solution quality. (reflection: do not quite understand how. What components will ensure one and the other? AARC - efficiency and DRO - quality of solution?).

Surgery Sequencing and Scheduling Problem (Seq_sched): After the assignment of the surgery cases from waiting list was done, a hospital manager allocate the surgeries in sequence by the start time. SO approaches for Seq_Sched with SICU/ ward capacity: Sequencing = single-provider SASS (Stochastic Appointment Sequencing and Scheduling). SASS is widely research complex stochastic combinatorial optimisation problem. Resetnly a novel SP solution was developed to enhance SASS. Some more literature that the author suggest to readers. SO approaches for Seq_Shed with PACU capacity: PACU are often overvelmed in high-paith scenario when surgery time is less then the patients recovery time. PACU > OR scheduling => downstream capacity blocking. Another direct voice of the author "Note that blocking is not clinically feasible for surgeries that require recovery in SICU because it is not possible to hold a patient in the OR for several days after surgery until a SICU bed becomes available." (reflaction: is it just theoretical assumtion?).

Page 11 (Modeling elective surgery scheduling problem): ... PACU admission policy can also be a constrain (i.e. what patient has a priority if two surgeries finishe at the same time?). Existing SO approaches:PACU metricies: patient waiting time, OR blocking time, OR finish and idel times. PACU staff overtime, and surgery cancellation. There are only two publications which cover multiple objectives at once (Table A.1 Appendix). Next three examples of Seq_sched PACU are discussed. Opportunity: The authors offered to analyse upper boundary for the PACU blocking time, since it it impossible completelly illiminate downstream blocking. In addition, the patient admission PACU policy such as FCFS (FIFO) and Critica-Patient-First (CPF) are prooved sibotimal approaches which can be enhanced. Then the authors propose an methods to deel with probable obsticles: (a) Composite Variable Modeling is a known method to reduce the size, remove complex objectives, and empover the LP relaxation of combinatorial optimisational problems; (b) Variable transformation - change how the LOS is represented in programming model; (c) Two-Stage Approximation - estimate scheduling by claculating it and comparing it within two policies: FCFS (FIFO) and (CPF). The final suggestion goes as a reminder of comparing the worst, and normal scenarios to render an optimsal scheduling considering both possible outcomes.

Some of the recent approaches (published between 2010 and 2020) to elective surgery scheduling under the block scheduling policy were. Note: this list is not comprehensive and is provided for illustrative purposes only.

	DT	LOS	DWU	# OR	SAAP	Sequencing	Metrics	Model	Sol. Approach
Denton et al. (2007)	✓			S		✓	OT, IT, WT	SP (SMILP)	Heuristics
Mancilla and Storer (2012)	✓			S		✓	OT, IT, WT	SP (SMILP)	heuristics
Berg et al. (2014)	✓			S		✓	OT, IT, WT	SP (SMILP)	ED, B&B-PH, SH
Shehadeh et al. (2019)	✓			S		✓	OT, IT, WT	SP (SMILP)	CPLEX
Jiang et al. (2017)	✓			S			OT, IT, WT	DR-MILP	ED
Mak et al. (2014)	✓			S		✓	OT, IT, WT	DR MISOCP	CPLEX
Shehadeh et al. (2020a)	✓			S		✓	OT, IT, WT	DR-MILP	CPLEX
Liu et al. (2019)	✓	✓	Ward	S			OT, IT	MDP	DP
Min and Yih (2010)	✓	✓	SICU	M	✓		OT SP (SMILP)	SAA-CPLEX	
Jebali and Diabat (2015)	✓	✓	SICU, Ward	M	✓		OT, IT, ExSICU, ExWard	SP (SMILP)	SAA-CPLEX
Jebali and Diabat (2017)	✓	✓	SICU	M	✓		OT, IT, ExSICU	2-stage CCSP	SAA-CPLEX
Zhang et al. (2019)	✓	✓	SICU	M	✓		OT, ExSICU	SP (SMILP)	SAA-CPLEX
Zhang et al. (2020)	✓	✓	SICU	M	✓		OT	SP (SMILP)	SAA-CPLEX
Neyshabouri and Berg (2017)	✓	✓	SICU	M	✓		OT, ExSICU	RO	C&CG
Moosavi and Ebrahimnejad (2018)	✓	✓	SICU, Ward	M			OT, IT, WTB, ER, LT	RO	MIP-based LNS
Shehadeh and Padman (2021)	✓	✓	SICU	M	✓		OT, IT, ExSICU	DRO	tractable C&CG
Hsu et al. (2003)	Deter	Deter	PACU	M		✓	Makespan, OT	Deter–MILP	TBS-based heuristics
Pham and Klinkert (2008)	Deter	Deter	PACU	M		✓	Makespan	Deter–MILP	CPLEX
Lee and Yih (2014)	✓	✓	PACU	M			WTB, WTA, OR, IT	FJS-FL	GA-based heuristics
Bai et al. (2017)	✓	✓	PACU	M			WTB, OT, ORBT, OT PACU OT	SimulationOpt	SGD
Lee and Yih (2012)	✓	✓	PACU	M		✓	WTB, WTA, OT, IT	Simulation	GA–based heuristics
Bai et al. (2020)	✓	✓	PACU	M			WTB, OT, IT, ORBT PACU OT	LR and SG	LR and SG
Gul et al. (2011)	✓	✓	PACU	M		✓	WTB, WTA, OT	Simulation	GA–based heuristics
Saremi et al. (2013)	✓	✓	PACU	M		✓	WTB, CT, SC	Simulation	TBS–based heuristics
Ewen and Mönch (2014)	✓	✓	PACU	M		✓	WTB, OT, IT	Simulation	GA–based heuristics

Notation: DT is surgery duration, LOS is length-of-stay, # OR is number of ORs, Deter is deterministic, WTB is patient waiting time before surgery, WTA is patient waiting time after surgery for PACU bed, OT is overtime, IT is idle time, ER is earliness, LT is lateness, ExSICU is cost of exceeding SICU capacity, ExWard is cost of exceeding ward capacity, ORBT is OR blocking time, PACU OT is PACU overtime, CR is patient's completion time, SC number of surgery cancellations, SP is two-stage stochastic programming model, SMILP is stochastic mixed-integer linear program, DP is dynamic programming, MDP is Markov decision process, SAA is sample average approximation, MIP-based LNS is Mixed Integer Programming based Local Search Neighborhood, CCSP is chance-constrained SP, RO is robust optimization, DRO is distributionally robust optimization, FJS-FL is flexible job shop with fuzzy logic, CG-based heuristic is Column-generation-based heuristic, C&CG is column-and-constraint generation, GA is Genetic Algorithm, TBS is Tabu search, LR is Lagrangian relaxation, SG is Subgradient method, ED is exact decomposition methods, B&B-PH is B&B with progressive hedging, Heuris-based BDecomp is heuristic solution approach based on Benders' Decomp, SH is sequencing heuristics, SimulationOpt is simulation optimization, SGD is sample-gradient descent. [a] Some models include patient-related cost. [b] With surrogate objective for sequencing.

Figure 1.64: Appendix from [14].

Page 12 (Future Research): There are a lot of research in this field, but need more and better. <u>Elective Surgery Databases</u>: There is a lot of medical records on surgery operation and PACU but it is no use unless it is preprocessed and stored in unified database system. The policy for structured data recording systems is required. The authors suggested to increase number of hospitals which use IT systems such as RTLS to track the capacity and resource availability (reflection: ask Anton for his londary project about RTLS). Enphasis of diversity of the origins of the timely records.

Page 13 (Future Research): Exploiting the Power of ML: Nowadays ML are efficient in solving tasks which envolve a big samples of data (the examples presented next). The downstide of the ML is their unpredictability and, relatively to defined methods, low accuracy. Sinse ML are hardly related to data to perform well, the best approach to generalise the ML model is to ensure that the process of building and adjusting ML in new envormenet can be replicated. Another good diraction is researching the adaptible ML (with self-tuning parameters). The Multi-Criteria and Cost Estimated Dilemma: Current multi-objective optimisation solutions articulate with multi-objective functions to design a scheduling. In reality, the objective types are fluid and can change overtime, which makes it harder for desicion-makers to use the MOOs. Some objectives are hard to specifically define and others are closely interconnected, which is also hard to treck. Therefore, sugested future research shold focus on narrowing the gap between MOO and real-world implementation as well as with balancing between expances, resource usage, and capacity...

Page 14 (Future Research): ... Preoperative activities, unpunctuality, and no-show. There is a flow of processes before an actual knife-to-skin surgery. The flow is different for inpatients and outpatients. PHU also can become a bottleneck. The patient latency and no-shows are sufficiently impact the flow of the surgeries further in the queue. Integrated approaches: The authors underline an importane of easy-to-use integrated desicion support tool for operating hospitals. "Some of the existing formulations often rely on big-M coefficients that take large values and undermine computational efficiency. Big-M is often used to relax some of the constraints or enforce certain conditions, among other uses (e.g., ensure that the waiting time of a patient is zero when the patient is not scheduled). Camm et al. (1990) provide specific guidance for practitioners interested in the ubiquitous big-M and provide many practical examples to demonstrate that almost always, there is a maximum theoretical and practical size for the big-M coefficients that can be derived using the structural properties of the problem. Such a smart choice of big-M value could improve the model solvability compared to using unnecessarily large values for this parameter, diminishing model tractability" (reflection: I copy the chunk of the paper again, since do not understand it). This scheduling task requires gread deel of coordination between the objectives. The available studies layed a good foundation for further scheduling solution development. Capacity planning during the period of high demand: Even advanced desicion support systems can not help if there is not enough well trained medical personnel, which was easy comfirmed by COVID19 crisis. There is yet to be more consideration what policy to follow in times of critical demand. Just increasing the number of ICU beds will not always an effective solution. There is already some studies in this diration.

Page 15 (Future Research): Decision support tools: A developed desicion support system should be effective and user-friendly. The proposedworkbanch E-HOSPITAL supports three level of desicion making and has several problems which can be solved. This tool is digital and is available for stakeholders and in pedagogical staff (healthcare analytics, service management, and information systems).

Page 15 (Conclusions): The curent review demonstrats a research on optimal stochastic elective surery scheduling with downstream capacities. The authors focus on three main approaches in the field: SP, RO, and DRO for the last decade (2010-2020). The uncertain surgery duration and postoperative LOS are critical criteria for consideration in effective scheduling advisory systems. Crusial points: (a) Lack of data-driven approaches; (b) There is no model which solves selection and assignment problems at the same time; (c) Lack of research which acknowledge the stohastic nature of the surgery duration and LOS, and consider the multimodal distribution of the durations; (d) There is great number of interconnected contraints, therefore no solution which can deel with all of them at once.(e) Scheduling considering SICU is easier and more researched than scheduling with PACU. (f) The authros proposed a few approaches which can overcome existing obsticles. Authors' suggestions: (1) Develop unified healthcare record system; (2) design data-driven ML- and optimisation-based approaches; (3) develop user-friendly and implementable tool for effective decision making; (4) consider methods for high-demand scenarios.

Chapter 2

Conclusions

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