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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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 ≈ 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.

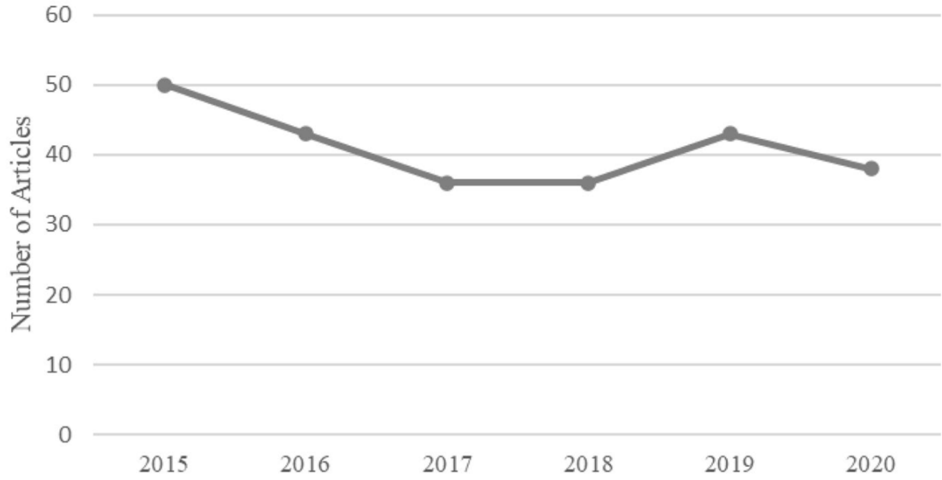


Figure 1.2: Number of articles per year [2].

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).

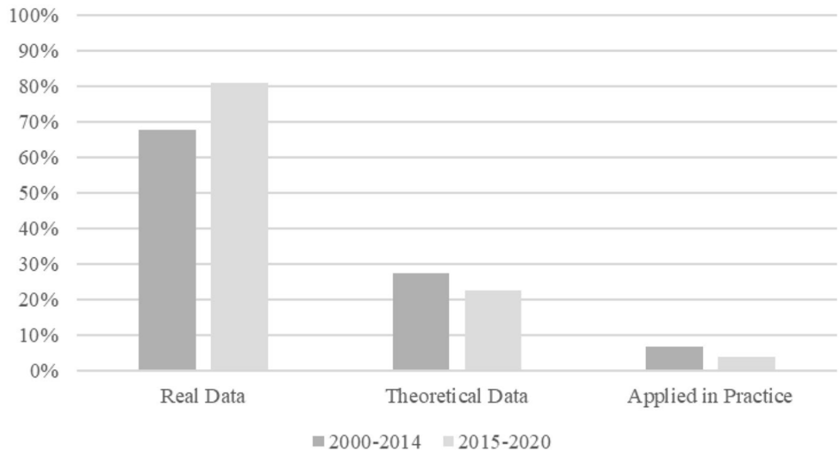


Figure 1.3: Testing and application from [2].

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.

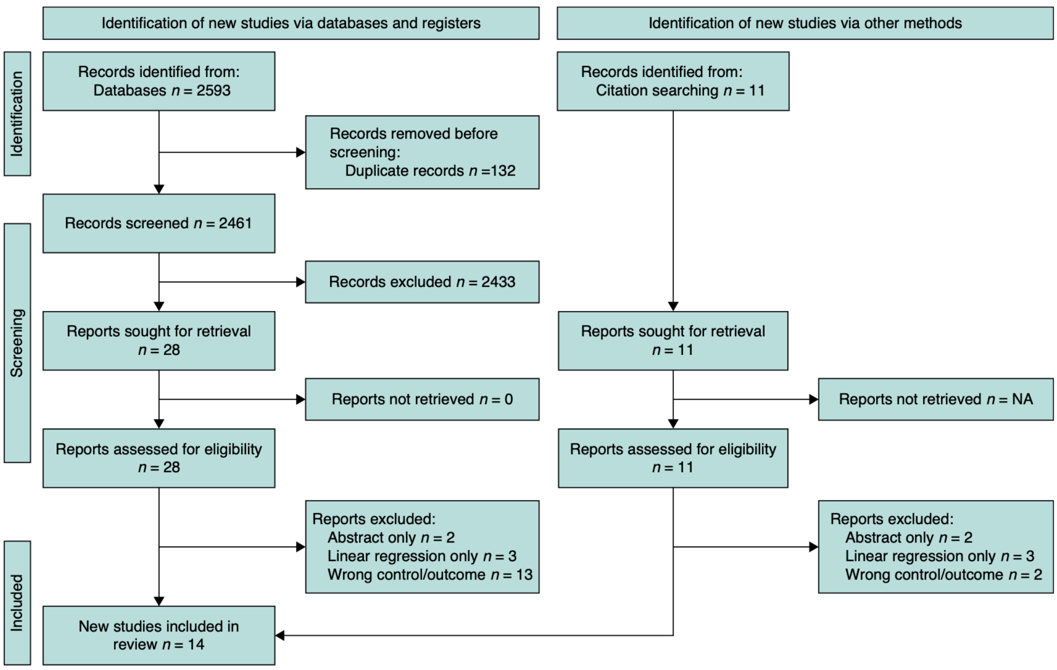


Figure 1.7: PRISMA diagram demonstrating the process of study selection, from screening to inclusion and the grey literature search (created using the online tool of Haddaway et al. (38)) from [3].

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).

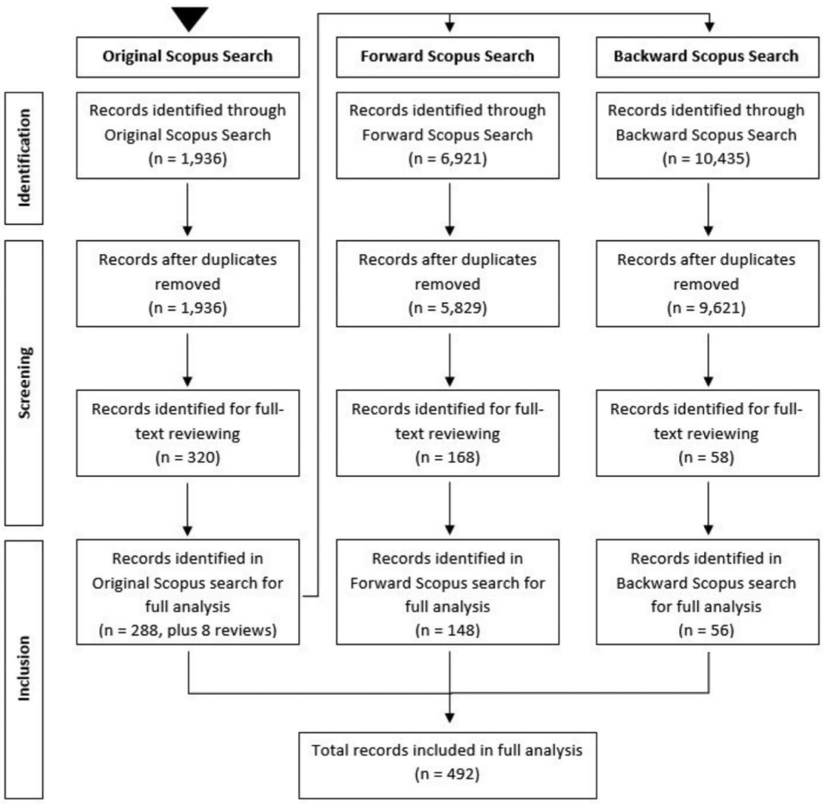
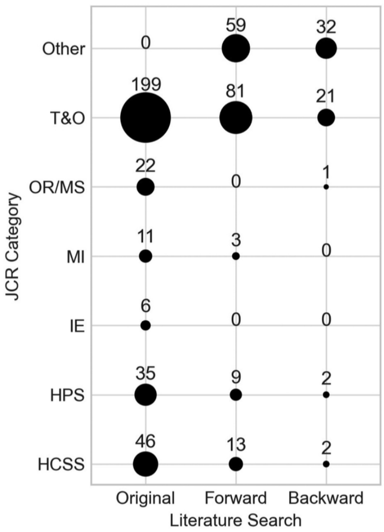


Figure 1.9: Flow diagram of the literature search in [4].

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.



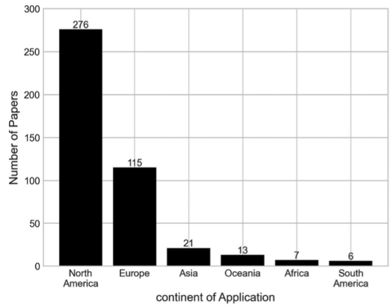


Figure 5. Number of papers by their continent of application.

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.

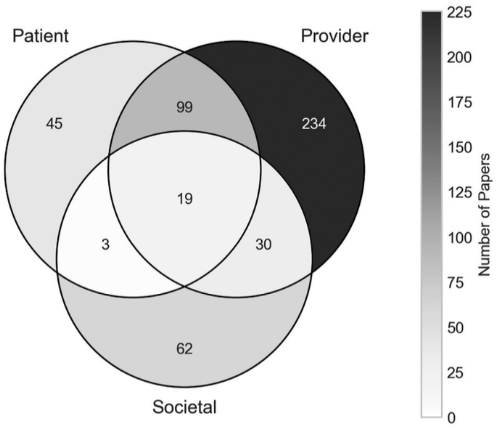


Table 1. Number of papers by their JCR category and planning decision level.

	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.

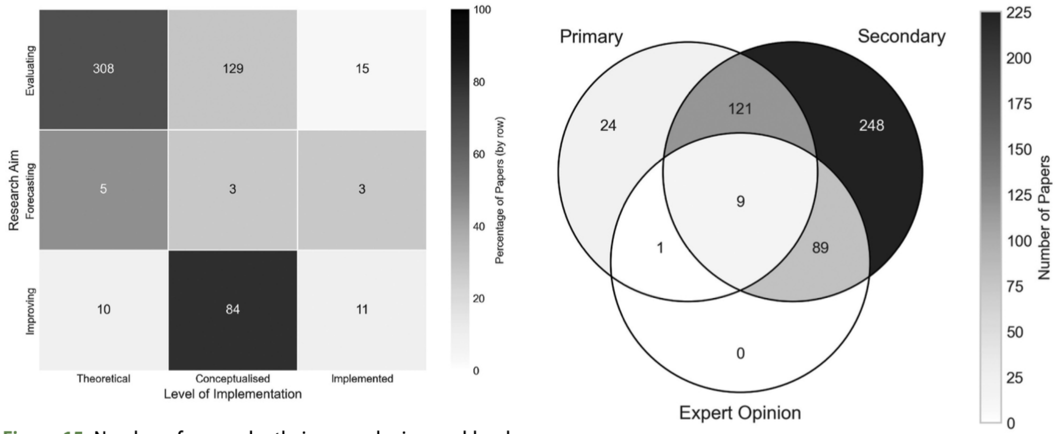


Figure 15. Number of papers by their research aims and level of implementation.

Figure 16. Number of papers by how the data was obtained.

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:

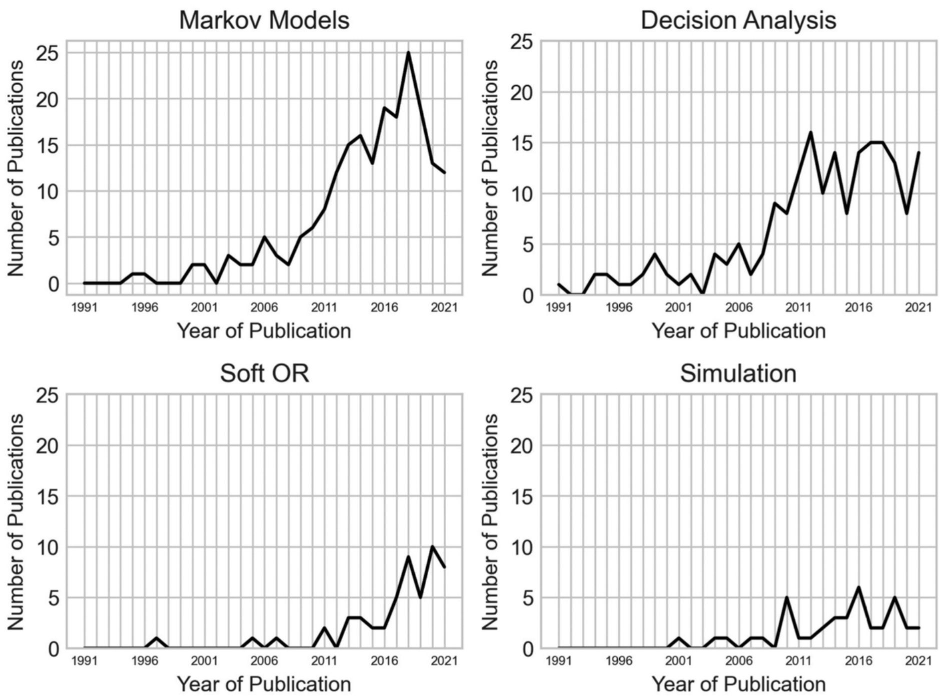


Figure 1.13: Trends from 1991 to 2021 from [4].

Page 19:

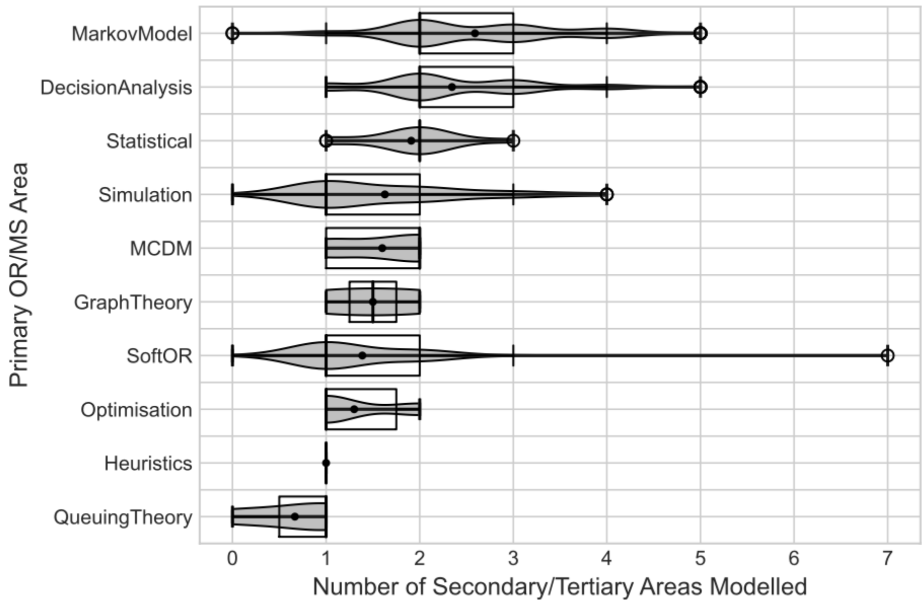


Figure 1.14: Number of papers by their primary OR/MS method area and level of implementation from [4].

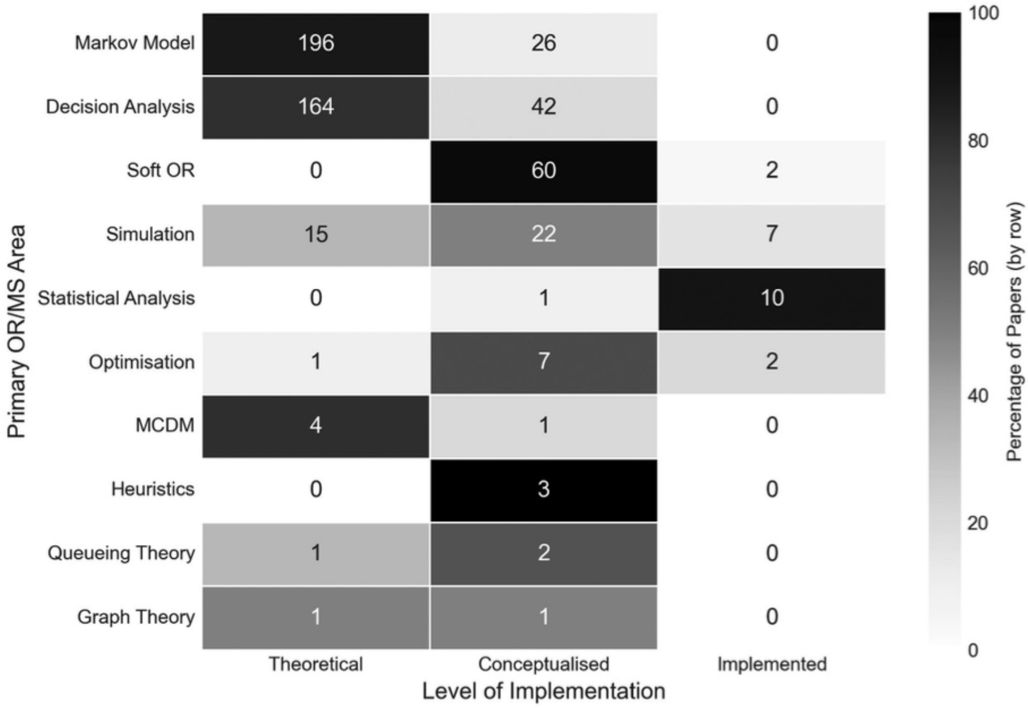


Figure 1.15: Distribution of the number of secondary/tertiary care areas modelled by each primary or area from [4].

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	85%	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.

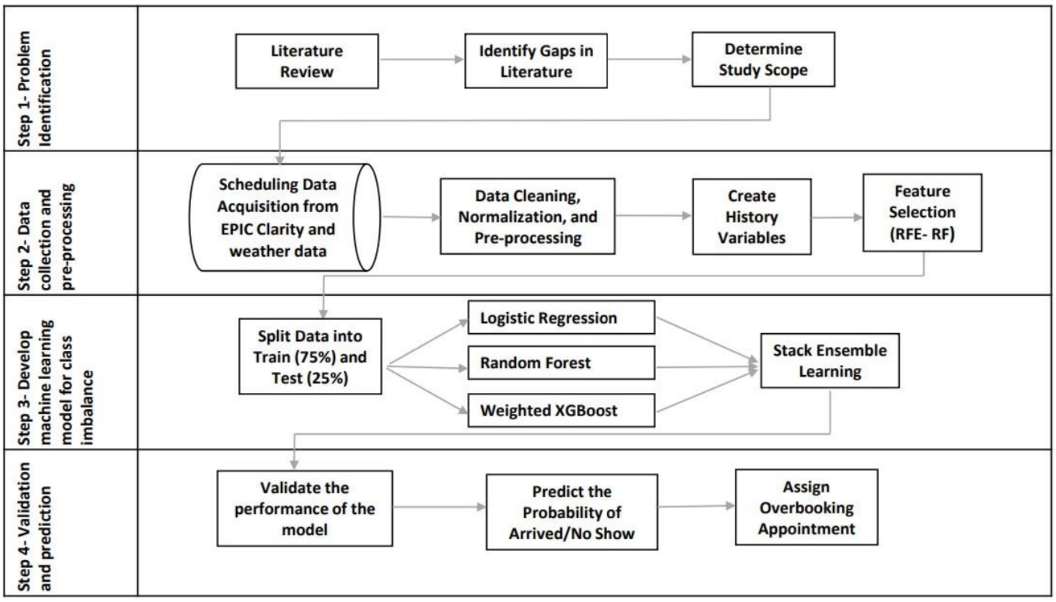


Figure 1.16: Research methodology framework from [5].

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.

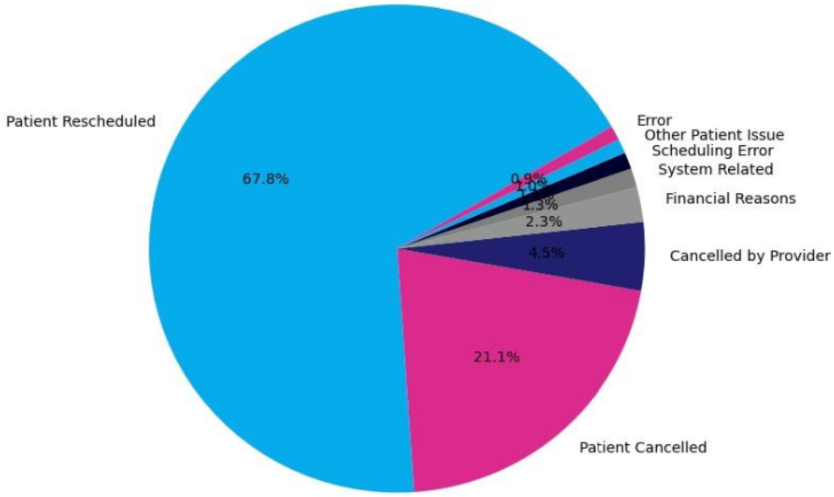


Figure 1.17: Research methodology framework from [5].

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].

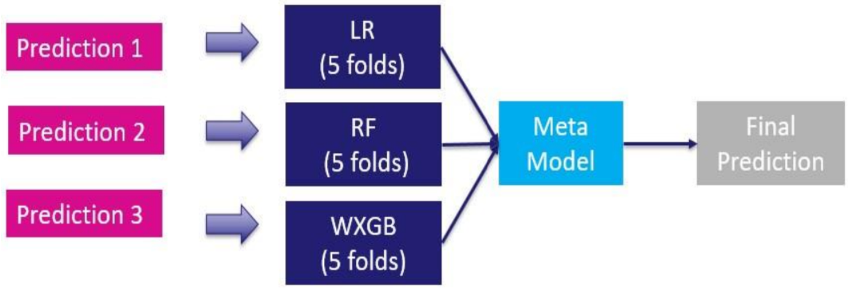


Figure 1.19: Architecture of the prediction model from [5].

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.

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

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

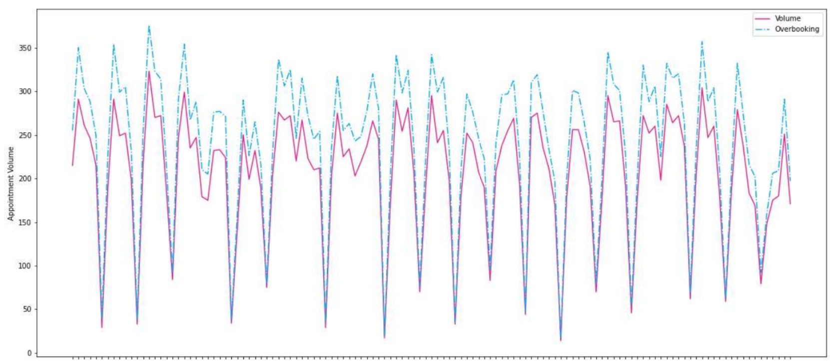


Figure 1.20: Overbook prediction in [5].

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.

Chapter 2

Conclusions

Bibliography

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