Utilizing Artificial Intelligence In Perioperative Patient Flow: Systematic Literature Review

University of Oulu
Department of Information Processing Science
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Huotari Anne
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Abstract

The purpose of this thesis was to map the existing landscape of artificial intelligence (AI) applications used in secondary healthcare, with a focus on perioperative care. The goal was to find out what systems have been developed, and how capable they are at controlling perioperative patient flow. The review was guided by the following research question: How is AI currently utilized in patient flow management in the context of perioperative care?

This systematic literature review examined the current evidence regarding the use of AI in perioperative patient flow. A comprehensive search was conducted in four databases, resulting in 33 articles meeting the inclusion criteria. Findings demonstrated that AI technologies, such as machine learning (ML) algorithms and predictive analytics tools, have shown somewhat promising outcomes in optimizing perioperative patient flow. Specifically, AI systems have proven effective in predicting surgical case durations, assessing risks, planning treatments, supporting diagnosis, improving bed utilization, reducing cancellations and delays, and enhancing communication and collaboration among healthcare providers. However, several challenges were identified, including the need for accurate and reliable data sources, ethical considerations, and the potential for biased algorithms. Further research is needed to validate and optimize the application of AI in perioperative patient flow.

The contribution of this thesis is summarizing the current state of the characteristics of AI application in perioperative patient flow. This systematic literature review provides information about the features of perioperative patient flow and the clinical tasks of AI applications previously identified.

Keywords
Artificial intelligence, perioperative, patient flow, clinical decision support, expert systems, workflow support

Supervisors
Ph.D., University Lecturer Karin Väyrynen, M.D., Ph.D. Janne Liisanantti

Foreword

First and foremost, I would like to express my sincere gratitude to my supervisors, Ph.D., University Lecturer Karin Väyrynen, and M.D., Ph.D. Janne Liisanantti, for their invaluable support and guidance throughout the entire thesis journey. I gained a comprehensive understanding of the process of conducting a systematic literature review from Karin Väyrynen. Janne Liisanantti's expertise in medicine and the perioperative process proved to be immensely beneficial to my research.

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Anne Huotari

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Contents

Abbreviations

AGI	Artificial General Intelligence
AI	Artificial intelligence
AIMS	Anesthesia information management system
ANI	Artificial Narrow Intelligence
ANN	Artificial neural network
CBR	Case-Based Reasoning
CDS	Clinical decision support
CDSS	Clinical Decision Support System
CNNs	Convolutional neural networks
CV	Computer vision
DL	Deep learning
EHR	Electronic health record
ICU	Intensive care unit
IS	Information systems
IT	Information technology
ML	Machine learning
NLP	Natural language processing
OR	Operating room
PACU	Post-anesthesia care unit
SLR	Systematic literature review
WFO	Watson for Oncology

1. Introduction

Some degree of Artificial intelligence (AI) has been present in our lives for at least a decade now. Many of us have used voice assistants like Siri and Alexa, or search engines like Google. We have used these apps to communicate with other people through messaging services like WhatsApp and Facebook, or to search the Internet for information we need. However, this technology has taken a significant leap forward in recent years with the introduction of deep learning (DL) algorithms that are capable of learning to perform tasks such as image recognition. Now, many technology companies are working on developing even more advanced forms of AI which have the potential to revolutionize the way we live and work. AI already outperforms humans in many tasks like playing chess and modelling protein structures. The healthcare sector holds great opportunities and promises, but fully utilizing the abilities of AI still involves many challenges. As AI evolves, we must consider its capacity for both good and bad consequences and take steps to ensure that it is used in ways that will benefit society. AI has been predicted to support healthcare, and it will be increasingly applied in the industry; AI has the potential to make patient outcome predicting, diagnosis, and treatment simpler and more efficient (Davenport & Kalakota, 2019).

While the volume of patient digital health data collected from many sources has increased over the past few years, so have opportunities to improve organizational effectiveness and patient flow based on correct data. The rapid increase in patient data from digital sources in health care organizations has altered the flow of patients through hospitals. Digital data can then be utilized to improve the processes and outcomes of patient care. AI-based applications are particularly promising in this context. However, the potential for using AI technologies in perioperative patient flow is still unknown. Having high velocity, high complexity, and high stakes, the perioperative environment is a high-risk area (Schimpff, 2007). According to Schimpff (2007), actual adverse events are very uncommon in an operating room (OR), but near misses are more frequent. One of Schimpff's (2007) suggestions for improving surgical site patient safety is to use new and effective information systems (IS). This study seeks for a response to what has previously been questioned about AI in perioperative care in order to support forming guidelines for utilizing the latest AI technologies in the perioperative process.

Several studies show that AI could be used to improve patient flow management. According to Gualandi et al. (2020), integrating numerous actors and processes is the biggest challenge. Markazi-Moghaddam et al. (2020) state that machine learning (ML) algorithms in clinical systems can support the consideration of the features of patient flow as well as surgical variables, while Bellini et al. (2022) introduce the idea that ML could help to estimate the length of hospital stay and ICU recovery. Mishra and Leng (2021) suggest DL algorithms could forecast and respond to potential negative outcomes as well as offer intraoperative counselling. AI applications in perioperative care could offer safe and timely treatment (Maheshwari et al., 2020; Bates et al., 2021) as well as real-time risk assessment and enable dynamic risk estimate throughout the perioperative episode (Bose & Talmor, 2018). According to Babtista et al. (2018), perioperative IS can enhance management effectiveness, decrease paperwork burden and medicine administration errors, lower expenses, and improve patient access to affordable healthcare. Explainable AI is topical in the health sciences (Holzinger et al., 2019; Bodenstedt et al., 2020), and requires contextual understanding and medical background. Domain expertise and the involvement of professionals such as computer scientists, clinical researchers, clinicians, and other stakeholders and users is crucial (Holzinger et al., 2019; Bodenstedt et al., 2020;

Bellini et al., 2022; Simon et al., 2019; Hashimoto et al., 2018; Lopez-Jimenez et al., 2020).

The need for this study arose in the Research Unit of Translational Medicine in the University of Oulu. As this kind of research had not been done before, a systematic literature review (SLR) was chosen as the methodology. The goal of this literature review is to map the existing landscape of the use of AI applications in secondary healthcare, with a focus on perioperative care. The review investigates what systems have been developed, and how capable they are of controlling patient flow. Patient flow management is a large entity involving the patient himself, his risks, other patients, and existing human and material resources. Perioperative care refers generally to the entire surgical process, from the time a procedure is being considered until long-term follow-up. Only those studies that included an assessment of outcomes linked to surgery and anaesthesia were included in this review. The review was guided by the following research question: How is AI currently utilized in patient flow management in the context of perioperative care?

This review presents the current state of AI solutions which have been tested or used in real life. Solutions from primary studies are analysed and primary functions are categorized a) based on the clinical decision support (CDS) taxonomy by Wright et al. (2011) and b) based on the new categorization this study has found.

Chapter 2 introduces a background for the context of this review and presents relevant research on patient flow management, AI, and perioperative care. The chapter covers the basics of the management of patient flow and perioperative care and clarifies how AI is currently utilized in CDS. Chapter 2 also describes how AI is classified into different categories and introduces challenges involved in the development of medical AI systems. Chapter 3 presents systematic literature review as the research method used in this thesis. Chapter 4 summarises the findings of the SLR and the identified categories of AI applications. The clinical tasks of the solutions are presented and classified. The chapter also introduces the research topics that emerged from the reviewed studies. Chapter 5 discusses the importance and relevance of the results. Chapter 6 presents the conclusions of the thesis as well as a summary of the results and reflections upon them. It also provides recommendations and displays the new knowledge contributed by the SLR.

2. Background

This chapter provides an overview of the subject area of the review. The present thesis includes discussion on patient flow management, artificial intelligence, and perioperative care. The relevant research at the intersection of these domains is presented in this section. Perioperative process and patient flow are defined. The perioperative process and patient flow are closely connected as delays in the perioperative process can directly impact patient flow throughout the process. The potential use of AI in perioperative patient flow is first discussed in Chapter 2.1. After that, Chapter 2.2 examines the role of AI in CDS. Chapter 2.3 presents the categorization of AI and Chapter 2.4 covers challenges involved in the development of medical AI systems. Chapter 2.5 summarizes the background.

2.1 Potential use of artificial intelligence (AI) in perioperative patient flow

This chapter describes the stages of the perioperative system, defines patient flow, and discusses potential ways to utilize AI in perioperative care patient flow. Perioperative care refers to the care activities that a patient receives before, during, and after surgery, including the preoperative, intraoperative, and postoperative stages (Erdogan & Denton, 2011). Figure 1 presents the stages of a perioperative system according to Erdogan and Denton (2011). They stated that the preoperative stage starts with the decision to have a surgery: it involves preparation for surgery, possible pre-visit to a preoperative clinic and the surgical suite intake process. It is followed by the intraoperative stage, which includes positioning the patient on OR bed, anesthesia and surgery. The postoperative stage starts with admitting the patient to a post-anesthesia care unit (PACU) or intensive care unit (ICU), followed by dischargement and follow-up visits in an outpatient clinic as long as needed. (Erdogan & Denton, 2011.)

Figure 1. Stages of a perioperative system (adapted from Erdogan & Denton, 2011).

Patient flow refers to the process in which patients move through the healthcare system from first contact to dischargement or completion of care (Nguyen et al., 2022). Optimizing patient flow can help reduce waiting times (Leviner, 2020), minimize delays (Ker & Wang, 2018), and improve access to care (Rylander et al., 2021), which can lead to better health outcomes for patients. Nguyen et al. (2022) recognized that health IS has been found to improve care coordination, identify bottlenecks, and streamline care operations by addressing problems in patient flow. They discovered that patient tracking, documentation management, order entry, patient registration, bed management, decision support, discharge management, prescription management and patient flow reporting were key components of health IS interventions that had an impact on patient flow. In the OR, delays regularly happen and have a significant impact on patient flow and resource utilization (Wong et al., 2010). According to Wong et al. (2010) perioperative delays, which include delays getting to the OR and delays during the procedure, happen on the day of the scheduled operation and prevent the best patient flow.

Gualandi et al. (2020) discussed potential improvements to the hospital patient flow. They conclude that since institutional, organizational, and patient-specific factors all play a role in determining hospital patient flow, it is complex and multidimensional. According to Gualandi et al. (2020), infrastructure, information technology (IT), and multidisciplinary teams are only a few organizational layers in which interventions can be made to optimize patient flow. Therefore, integrating numerous actors and processes is the greatest challenge. Design and implementation of complex, multidimensional and coordinated interventions is necessary to optimize hospital patient flow (Gualandi et al., 2020). Daily surgical OR scheduling entails opportunities to exploit the variations in surgery types and recuperation times to avoid standstills in patient flow. Markazi-Moghaddam et al. (2020) conclude that staff can identify patients who may need a lengthy stay in the OR by using precise classifiers that consider both patient features and surgical variables. Adopting ML algorithms in clinical systems can support these kinds of solutions (Markazi-Moghaddam et al., 2020).

Bellini et al. (2022) discussed the utilization of ML technology in perioperative care. They state that a customized risk/benefit analysis can produce an exact estimate of the length of hospital stay and ICU recovery, which will have a favourable impact on patient care and medical expenditures. Mishra and Leng (2021) discussed retinal surgery, concluding that AI has a role in enhancing safety and efficiency to improve patient outcomes. They suggest that DL algorithms could forecast and respond to potential negative outcomes as well as offer intraoperative counselling.

According to Maheshwari et al. (2020), AI applications in perioperative care could offer safe, timely and cheap treatment, and perioperative intelligence concentrates in three major areas: detection of at-risk patients, early diagnosis of complications, and well-timed and efficient treatment. Correspondingly, Bates et al. (2021) studied AI's potential to improve patient safety. Their insight was that prognosis and prevention of surgical complications could be moderately impacted by the AI, both in the OR and during recovery.

Babtista et al. (2018) conclude that surgical operations are major contributors to patient morbidity, mortality, satisfaction, and total hospital expenditures and profitability. They suggest that perioperative IS can enhance management effectiveness, decrease paperwork burden, decrease medicine administration errors, lower expenses, and improve patient access to affordable healthcare. Babtista et al. (2018) recognized in their overview that coordination and management of surgical equipment and surgical patient preparation processes have been found to benefit from automation and IT.

Nguyen et al. (2014) elaborated that an electronic health record (EHR) is referred to as a virtual record of every health-related event (such as a hospital admission, a visit to a general practitioner, or allergies etc.) that a person experiences throughout their lifetime, from birth to death, and EHRs are also referred to as any sort of electronic medical records. Bose and Talmor (2018) reviewed and summarized future directions for integrating ML algorithms into EHR systems, stating that it could offer real-time risk assessment and enable dynamic risk estimation throughout the perioperative period. Lu et al. (2017) discussed timeline-structured clinical data systems and visual analytics for supporting decision making, recognizing that clinical records, medical and health research records, administrative information, and financial information are all examples of data that may be used in the healthcare industry. According to Lu et al. (2017), the increasing amount of data brings the challenges of pre-processing, warehousing, and mining the data as well as visualizing it for maximum user benefit. Lu et al. (2017) defined data warehousing as a method for combining data from many operational systems to produce population-based perspectives of health data. They conclude that by focusing resources on more effective therapies, data mining and visual analytics could help patients receive optimal care.

2.2 Artificial intelligence (AI) in clinical decision support

Clinical decision support (CDS) refers to the use of technology and relevant patient information to aid in medical decision-making and improve healthcare delivery (Sutton et al., 2020). According to Wasylewicz and Scheepers-Hoeks (2019), many kinds of computerized and non-computerized tools and interventions are included in CDS. High-quality clinical decision support systems (CDSS), also known as computerized CDS, are required to harness the total benefits of EHRs and automated physician order entry (Wasylewicz & Scheepers-Hoeks, 2019).

Today, AI can play a significant role in CDS. CDSSs are described as software intended to be a direct aid to clinical decision-making (Sim et al., 2001). According to Sim et al. (2001), these systems compare a patient's features to a computerized clinical knowledge base, and then provide the doctor or the patient with patient-specific assessments or suggestions.

Earlier AI decision support solutions are built to give simple alerts based on clinicians' basic workflows. According to Miailhe and Hodes (2017), these kinds of tools are called Artificial Narrow Intelligence (ANI, also called "weak" AI), as they are working by the rules programmed into them. Ward et al. (2022) as well as Miailhe and Hodes (2017) discussed ANI, recognizing that currently AI only does a limited set of tasks so that computers can successfully do a few particular duties. One example was IBM's ambitious effort to build a clinical AI solution, computer Watson, which Strickland (2019) called an "AI superdoctor". Fjelland (2020) described how it was originally developed with the goal to win the US TV show "Jeopardy!". Shortly after Watson had won the quiz, IBM decided that Watson should become an AI medical superdoctor and transform medicine. Fjelland (2020) added that IBM had the idea that if Watson had access to all medical literature such as health records, textbooks, journal articles, and lists of drugs, it should beat human doctors in giving accurate diagnosis and treatment. IBM participated in various projects, but the success was limited; projects failed and were closed. Developing an AI doctor was not so easy as some had assumed. Strickland (2019) argued that in place of superdoctors, IBM's Watson Health has produced AI assistants capable of doing routine tasks.

According to Bharadwaj et al. (2013), big data refers to data collections that are too large to be captured, managed, and processed by typical software tools in a given amount of time. Big Data and AI have the potential to have a significant impact on our future (Benke & Benke, 2018). Benke and Benke (2018) argue that with the broad adoption and integration of these technologies, the position of the medical specialist will be challenged. Considering the next steps in AI development requires questioning whether achieving Artificial General Intelligence (AGI, also called "strong" AI) is possible in the first place. According to Miailhe and Hodes (2017), AGI can be described as a technology that has the potential to rival human intelligence. However, experts disagree about whether this will happen in the coming decades, or ever.

Wang et al. (2020) studied how clinical decision-making techniques are applied in the pediatric ambulatory and inpatient contexts. Nowadays the majority of patient data is stored in the hospital's repositories. Wang et al. (2020) conclude that future data sources may be patient-reported outcomes by outpatients themselves and real-time data from wearable devices. They suggest that clinical decision-making breakthroughs are advancing at a noticeably faster rate as advances in AI and ML are applied to ever-larger datasets. In contrast, Han and Tian (2019) addressed image interpretation as one of the popular fields of AI research, which aids radiologists in increasing diagnostic accuracy and reducing mistakes and observer fatigue. They listed predicting a patient's clinical outcome using a clinical dataset, genomic data, and medical pictures as other significant applications for AI in healthcare. Han and Tian (2019) state that AI could overcome challenges in risk assessment and outcome prediction. Hospital systems are already utilizing technologies like natural language processing (NLP) to obtain diagnostic data from reports like radiology, pathology, and clinical notes (Lopez-Jimenez et al., 2020).

The Nordic State of AI report from 2021 scoped the state of AI in the Nordic countries. According to the report, building business models and the activities of organizations around AI is becoming more common. Only a supporting technology in the past, AI is nowadays a salient strategic asset for companies. The report investigated the implementation of AI in different industries. Unexpectedly, the healthcare industry is not included in the top 10. In conclusion, The Nordic State of AI report declares that the Nordics are a forerunner in the field, especially in overall AI readiness, along with AI ethics and trustworthiness.

2.3 Categorization of Artificial Intelligence (AI)

This chapter is dedicated to describing the different categories and classification of AI. According to Collins et al. (2021), AI in IS research is still substantially underdeveloped. A thorough analysis of what is known about AI in IS remains to be done, even though a large volume of literature deals with AI in some capacity. Collins et al. (2021) recognize that the description of AI in IS remains inconsistent.

The concepts and types of AI are described in the following discussion. Figure 2 presents general branches and definitions of AI types found in related literature. These are ML, neural networks, NLP, rule-based expert systems, computer vision (CV), fuzzy logic and robots and robotic process automation. DL is a class of ML (Benbya et al., 2021). Convolutional neural networks (CNNs) are utilized in CV for the classification and processing of images.

Ward et al. (2022) discussed AI fields regarding surgery. They defined ML as a field of study within AI that aims to teach computers and machines how to learn. Ward et al. (2022) described neural networks, explaining that the data itself is used to draw conclusions without the need for manual feature selection; it is made up of even thousands of computer-represented "neurons" that are either on or off, much like the structure of the human brain. DL involves multiple processing layers which detect complicated and hidden patterns. The domains of language processing and image recognition have been significantly transformed by the use of DL. Researchers have started implementing NLP in a variety of medical applications, especially those linked to the electronic medical record. Computers can now accurately model and understand language. CV means training a computer to recognize and understand photographs. CNNs are a specific type of neural network structure. The visual cortex of a human is analogous to how CNNs operate. They allow the classification of the parts of an image into the essential elements required for recognition, such as shape, texture, and color, without having to process every pixel of data. Visual aspects of medicine, from image-based diagnostics to real-time surgical video analysis, have been deployed as a result of CNNs. They have also acted as the inspiration for much of the recent success and the rising popularity of artificial intelligence in surgery. (Ward et al., 2022.)

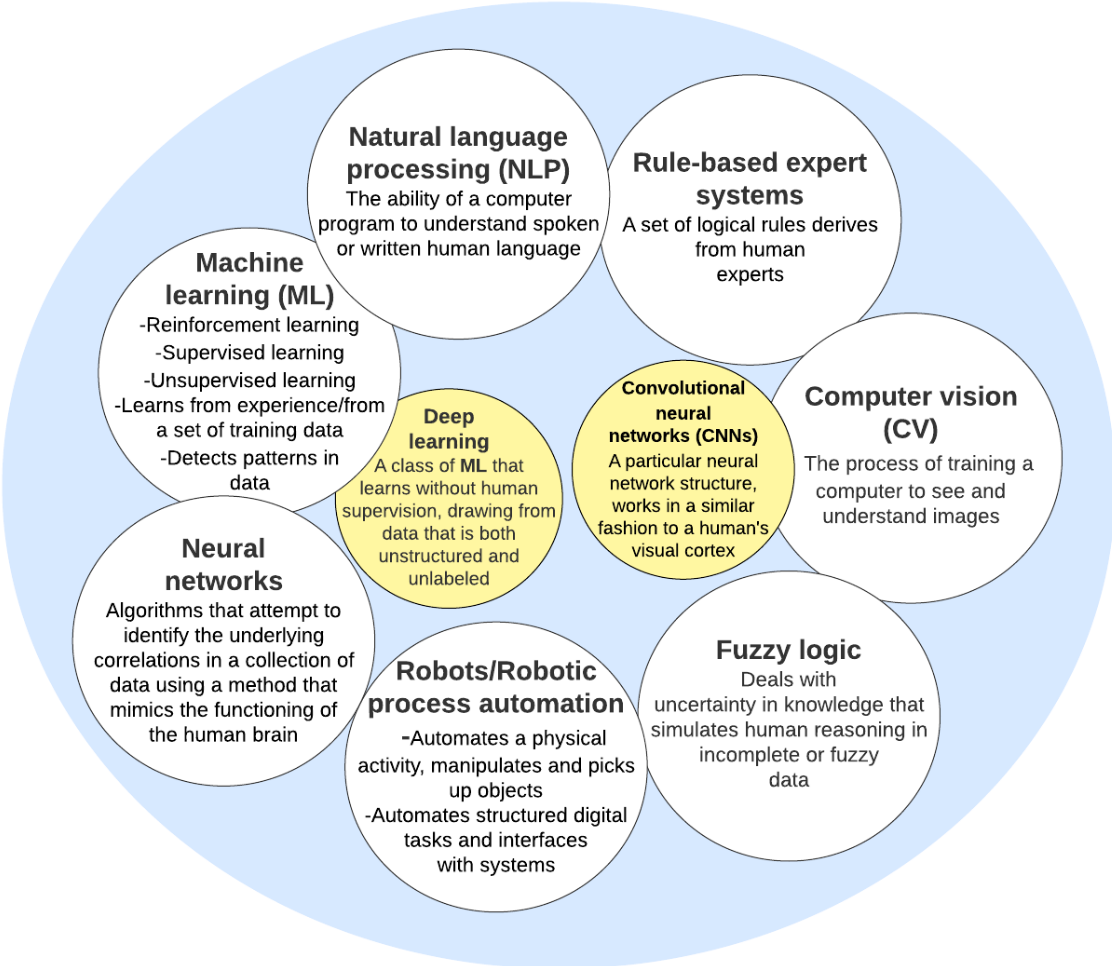

Figure 2. Definitions of AI, based on Benbya et al. (2021), Ward et al. (2021), Saleem (2008).

Saleem (2008) state that Fuzzy control works best when used for production processes that primarily rely on human intuition and experience, hence excluding the use of traditional control techniques. Panesar et al. (2019) studied robots and AI in the surgical context: their conclusion is that by the end of the 21st century, clinically useful surgical robots will likely be developed. The expansion of surgical capability to improve outcomes and broaden access to care may be made possible by the combination of AI and surgical robotics (Panesar et al., 2019). According to Grosan et al. (2011), rule-based systems, often called production systems or expert systems, are the most basic type of AI. Rule-based systems imitate the knowledge-intensive problem-solving process of a human expert and consist of a set of guidelines that specify what to do or what to conclude in certain circumstances: a series of if-then statements which are used to represent rules (called IF-THEN rules or production rules) (Grosan et al., 2011, p. 149).

2.4 Challenges with medical artificial intelligence (AI) systems development

Holzinger et al. (2019) discussed explainable AI which is topical now in medicine, expressing concerns about losing control in Human-AI interaction. According to Holzinger et al. (2019), algorithms can be called "black box" models, as understanding how algorithms are designed and what is their function is very challenging for users.

The lack of transparency in AI algorithms used in medicine poses a significant challenge for patient communication and trust when a patient is informed of a diagnosis but even doctors cannot explain the decision (Davenport & Kalakota, 2019). Davenport and Kalakota (2019) estimate that for many years to come, AI will need constant monitoring and careful policymaking: AI systems need to be approved by regulators, integrated with EHR systems and sufficiently standardized. They advise healthcare organizations, governments, and regulatory bodies to set up systems to keep an eye on important issues, respond responsibly, and set up governance frameworks to keep negative consequences to a minimum.

Holzinger et al. (2019) discussed the question of the scope of AI and how it could or should assist medical decisions, or even make them. They distinguished causability as the ability of a person, such as a medical professional, to understand the cause-and-effect relationships underlying a decision or outcome, whereas explainability means the capacity of an AI system to provide meaningful explanations for its decisions or predictions. Holzinger et al. (2019) also emphasize the importance of human expertise in health informatics; long-term experience can assist in problem solving. To examine the total influence of AI on perioperative risk assessment and other health care contexts as well, Bellini et al. (2022) recommend the healthcare industry and AI developers adopt a multidisciplinary and systemic approach.

Bodenstedt et al. (2020) conclude that including stakeholders like clinicians, engineers, patients, and industry allows problem solving and enhanced patient care regarding AI-assisted surgery. Bodenstedt et al. (2020) state that developing explainable AI instead of "black boxes" requires contextual understanding and medical background; this makes judgments more transparent and easier for users to follow. Simon et al. (2019) also recognize how essential domain expertise is in the development of useful AI applications. AI experts should be cross-trained clinical and AI experts. Simon et al. (2019) state that as the development of AI for medicine involves knowledge from both the clinical and technical fields, it depends on partnerships between industry and academia. According to Simon et al. (2019), clinical leadership will be needed, and domain expertise is critical since there may be disagreements between the technical and clinical perspectives.

Hashimoto et al. (2018) conclude that surgical practice is unique, and surgeons are in a key role to help develop the next generation of AI. They suggest that surgeons should collaborate with data scientists to collect data from all phases of patient care and to give clinical context, adding that AI has the potential to change surgical education and practice. According to Hashimoto et al. (2018), AI holds the promise of a future where patient care is maximized at the highest possible level. Lopez-Jimenez et. al (2020) summarize that AI demands strong cooperation between computer scientists, clinical researchers, clinicians, and other users to determine the most relevant issues that need to be resolved as well as the most effective strategy and data sources for doing it.

2.5 Summary of the background

Perioperative care consists of three phases: preoperative, intraoperative and postoperative. Because each stage has many steps and stakeholders, perioperative care is complex and patient flow involves many aspects to consider. Previous studies have identified needs, weaknesses and development possibilities in the perioperative patient flow.

Perioperative care could benefit from AI in minimizing wait times, delays, and improving access to care. There are also other areas where clinicians could be helped. Pre-processing, warehousing, and mining data with the help of AI are topical issues in IT and health industry. Fetching patients' EHR data from many sources and integrations to the perioperative process are crucial. When the operational activities of these areas are assisted by AI, the use of resources can be better allocated as needed. These actions will also have an impact on improving patient safety and patient outcomes. Table 1 presents possible interventions or features in health IS and in perioperative care. which researchers suggest may influence the patient flow.

Table 1. Interventions and features recognized in research as having impacts on the patient flow

Author (year)	**Interventions/features that have impacts on the patient flow**
Nguyen et al. (2022)	Patient tracking, documentation management, order entry, patient registration, bed management, decision support, discharge management, prescription management and patient flow reporting
Markazi-Moghaddam et al. (2020)	Precise classifiers that consider both patient features and surgical variables, for identifying patients who may need a lengthy stay in the OR
Bellini et al. (2022)	Customized risk/benefit analysis that produces an exact estimate of the length of hospital stay & ICU recovery and will have a favourable impact on patient care and medical expenditures
Mishra & Leng (2021)	Forecast and respond to potential negative outcomes, intraoperative counselling
Maheshwari et al. (2020)	Detection of at-risk patients, early diagnosis of complications and well-timed and efficient treatment
Babtista et al. (2018)	Coordination and management of surgical equipment and surgical patient preparation processes
Lu et al. (2017)	Timeline-structured clinical data systems and visual analytics for supporting decision making
Bates et al. (2021)	Improving patient safety, prognosis and prevention of surgical complications
Bose & Talmor (2018)	Real-time risk assessment

AI has many categories that are already utilized in the CDS. Techniques like ML, DL, NLP, CV, CNNs, rule-based expert systems and robotics already offer many solutions in the healthcare industry. Medical AI systems still have many challenges to be taken into account and solved. Explainability, transparency in algorithms, policymaking and regulation are the issues which raise debate about AI solutions. The perioperative patient flow setting is a complex and critical part of hospital operations. Both clinical and technical understanding and cooperation are needed when developing AI systems in perioperative care.

3. Research method and process

To get an overview of the current situation regarding the use of AI in the health care system and particularly in perioperative healthcare, a systematic literature search was conducted. This chapter introduces the method of Systematic literature review (SLR) and describes how the methodology was conducted in this thesis. First, an outline of the research methodology and its key stages are presented. The remainder of the chapter elaborates each phase of my work.

3.1 Fundamentals of SLR

SLR is a process that identifies, organizes, and evaluates all literature on a given topic. In the SLR guidelines, the process involves three main phases: planning, conducting, and reporting the review (Xiao & Watson, 2019; Kitchenham & Charters, 2007).

Okoli (2015) listed eight steps to conduct a SLR, which are described in the Figure 3. According to Okoli (2015), in order to create a thorough literature review, reviewers must clearly identify the purpose of the review, draft a protocol, train the team, and apply a practical screen. Researchers need to be explicit in describing the details of their literature search as well as explain and justify how they assured the comprehensiveness of the search. They need to systematically extract the applicable information from each study, and then score all included papers for their quality. The last step is synthesizing all the data extracted from the studies and writing the review. (Okoli, 2015.)

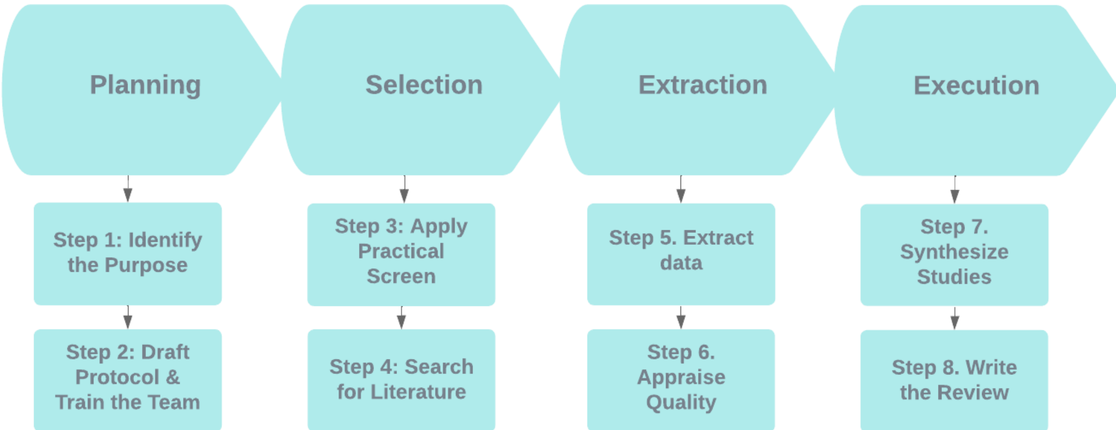

Figure 3. Process of Systematic literature review, based on Okoli (2015, p. 885).

According to Xiao and Watson (2019), searching the literature and screening for inclusion progresses from reviewing titles to reviewing abstracts and full texts. Each step will elaborate and limit the research population (Xiao & Watson, 2019). The SLR process can improve the quality, reproducibility, reliability, and validity of the review (Xiao & Watson, 2019). According to Kitchenham and Charters (2007), the guidelines of many SLRs support evidence-based medicine. They pursued to develop principles for undertaking SLRs that are appropriate to the needs of software engineering researchers. Kitchenham and Charters (2007) listed the most common reasons for conducting an SLR:

- Summarizing the evidence of a treatment or technology.
- Finding gaps in the existing research and recommending areas for additional study.

- Offering a foundation or context in order to situate new research initiatives properly.

3.2 Planning the review

Planning the review includes the steps of formulating the problem, developing and validating the review protocol, and training the team (Okoli, 2015). This chapter describes how the need for a review was identified in the present thesis. The research question and need for the SLR are elaborated, followed by a description of how the draft protocol was created and how the team was trained in this SLR.

3.2.1 Research question and need for the SLR

Kitchenham and Charters (2007) argue that the most crucial step in any systematic review is to clearly define the research questions. These are what guides the systematic review process. The methods used for data extraction and synthesis, as well as the studies included in the review and reporting, should all be directed toward addressing the research questions (Xiao & Watson, 2019). Okoli (2015, p. 887) state that first step of conducting a literature review is defining its purpose, which should answer the question “Why do a literature review”.

The need for this study arose in the Research Unit of Translational Medicine in the University of Oulu. There was a need to map the existing landscape of the use of AI applications in secondary healthcare, with a focus on perioperative care. The review investigates what systems have been developed, and how capable they are of controlling patient flow. Patient flow management is a large entity involving the patient himself, his risks, other patients, and existing human and material resources. To further investigate the use of AI in perioperative care and in patient flow, more research is required. As this kind of research had not been done before, a systematic literature review (SLR) was conducted to extract and analyze AI approaches employed in the context of perioperative patient flow.

Perioperative care refers generally to the entire surgical process, from the time a procedure is being considered until long-term follow-up. Only those criteria that included an assessment of outcomes linked to surgery and anaesthesia were included for this review. The review was guided by the following research question: How is AI currently utilized in patient flow management in the context of perioperative care?

3.2.2 Draft protocol and training the team

According to Okoli (2015), before reviewers can begin working on the review, the reviewers must complete one more crucial task in the preparation phase: they must create a protocol and externally validate it to ensure its validity. Reviewers must be completely clear and in agreement on the approach they will follow for every review that involves more than one reviewer, which requires both a written, comprehensive protocol document and training for all reviewers to ensure consistency in how they carry out the review (Okoli, 2015). Karin Väyrynen and Anne Huotari started the master’s thesis process by discussing the possible review type. The SLR was chosen because it seemed like a natural way to map the current state-of-the-art in the field of AI and perioperative care. This SLR followed the basic steps of the SLR process, which are presented in Figure 3. These steps were planned together in the meetings with supervisor Karin Väyrynen and the author. The steps were discussed additionally in email conversations, so that the two supervisors and the author were all up to date on how the SLR is processing. Meetings and email conversations were also the way of training reviewers on the scope of this SLR.

3.3 Selection of the studies

This chapter describes data sources and search strategy as well as the searching of literature and screening for inclusion in this SLR. First an initial search was done. The SLR was done iteratively: first initial search of the literature was performed, and after that the content of the 50 first search results was analyzed. After analyzing the initial search content, the search string was refined. When the search string was refined, the final search of the literature was conducted.

3.3.1 Initial search of literature

The objective of a systematic review is to use an unbiased search method to locate as many primary studies as feasible that address the research topic (Kitchenham & Charters, 2007). Kitchenham and Charters (2007) state that iterative search strategies are typical and benefit from preliminary searches, various combinations of search terms in pilot searches, refinement of search strings and consultation of experts on the field.

A generic search string addressing the research question was formulated to be used in selected database libraries. Building the search string began in January 2022. At first, Google Scholar was used to search for SLRs on "artificial intelligence" and "patient flow". That was a way to find out what type of articles have been published on the topic before. The first search string was based on the keywords that earlier SLR studies have used as keywords to search for "patient flow", "AI", and/or "perioperative" in their own systematic searches. The 14 studies which were used for building the search string of the SLR are listed in Appendix A. One of those was about the perioperative theme, nine about AI and three of them had a patient flow theme. Additionally, Janne Liisanantti's clinical experience of perioperative care and patient flow was utilized in building the search string.

Preferred databases for the search were discussed with the supervisor. We decided that information sources used in searches included scholarly databases of peer-reviewed articles on

- Scopus,
- Web of Science,
- Ovid MEDLINE, and
- PubMed.

The preliminary string was tested, and 1410 results were found. The results were exported and added on Covidence, which is a systematic reviews production tool for title, abstract and full-text screening, data extraction and quality assessment. After duplicates were removed, the result was 798 articles.

Xiao and Watson (2019) state that it is suggested to have at least two reviewers who work independently. Assessing the studies to match the inclusion and exclusion criteria is beneficial (Xiao & Watson, 2019). According to Xiao and Watson (2019), discovering the research question can be an iterative process.

The quality and result group of articles were reviewed together with the supervisor, by analysing the content of the 50 first search results. Screening the literature at that point was performed as follows: we tabulated search results in Excel and made an independent estimation of each article, deciding whether it should be included or not. The selection criteria in that phase were:

- Exclusion criteria: Is a review / Is commentary paper / Is pre-print (not accepted paper) / Is not about AI
- We had three research questions in the first screening phase, with the initial search string. We considered those all so that we could have a broad view for the review, and that we could also collect background material for the review. Based on the research questions at that point, we elaborated also whether our estimation was based on the abstract or whether the full text was reviewed. The research questions were:
    - RQ1: How is AI currently utilized in patient flow management in the context of perioperative care?
    - RQ2: What should be taken into consideration when utilizing AI in patient flow management in the context of perioperative care?
    - RQ3: What are potential solutions or algorithms that would/could benefit patient flow management in the context of perioperative care?

After analysing the first search results, I started the search string refinement phase. The refinement phase was iterative and consisted of the following tasks:

- I analysed papers from the first, initial string and looked what search terms related on perioperative care were found.
- I added terms from certain papers which were related to perioperative care and patient flow.
- Terms from the first search string were refined. Unnecessary limiting factors were edited out of the search string, for example “urgent surgery”, “emergency surgery” was shortened to “surgery”, and “perioperative care”, “perioperative medicine”, “perioperative process” was shortened to “perioperat*”.
- Patient flow keywords were still added, and perioperative and artificial intelligence keywords were elaborated.
- I consulted Janne Liisanantti from the Research Unit of Translational Medicine regarding perioperative care and patient flow search terms.

3.3.2 Search for literature

After the initial search, the research question was narrowed down and RQ1, “How is AI currently utilized in patient flow management in the context of perioperative care?”, was used when searching the literature. The final terms in the search strategy are shown in Table 2. Three categories of keywords were used. The first group consisted of patient flow terms. The keywords in the second group were perioperative-related terms. The third group of keywords had AI-related terms, including “artificial intelligence,” “machine learning,” and “deep learning”. The term “AI” encompasses a variety of AI-related concepts as well as specific AI methods including neural networks, support vector machines, decision trees, and NLP. Yet, research utilizing these methods will very likely use “artificial intelligence” or “machine learning” in their abstracts or keyword lists.

The search strings for each database are presented in Appendix B. The final search was executed in four databases in March 2022. The search results were added as a new search in Covidence. The search result was 4585 articles, and after duplicates were removed, 2716 articles in total were in the material.

Table 2. Search terms used in the SLR.

	AND		
	Patient flow	**Perioperative**	**AI**
OR	patient flow	preoperat*	artificial intelligence
	flow of patients	postoperat*	big data
	patients' flow	intraoperat*	machine learning
	patient transfer	perioperat*	deep learning
	patient process	pre-operat*	pattern recognition
	flow of care	per-operat*	automated intelligence
	patient admission	peri-operat*	data mining
	organizational efficiency	post-operat*	neural network*
	access time	intra-operat*	computer assisted diagnosis
	bed occupancy	operating theatre	computer-assisted diagnosis
	capacity allocation	operating room*	computer-aided diagnosis
	capacity management	surgery	computer aided diagnosis
	capacity planning	surger*	
	care management	surgic*	
	patient pathway	emergency service	
	patient route	post anasthesia care unit	
	patient throughput	operative triage	
	process flow	anesthe*	
	wait time	anaesthe*	
	waiting list	trauma	
	waiting time	enhanced recovery	
	length of stay	rapid recovery	
	care access		
	demand management		
	clinical pathway		
	treatment pathway		
	patient journey		
	patient care process		
	patient flow logistic*		
	key performance indicator*		
	lean healthcare		
	patient turnover		
	length of stay		
	caseload		
	workload		
	decision support		

The search was conducted in English. No restrictions were made on the study design or year of publication. The screening process was done in three steps. First, duplicated items were removed in Covidence automatically (n=1869). Secondly, articles were screened based on the headings and abstracts (n=2716). Studies that were not about AI, lacked real-world solutions or a user interface were not included in the review. Studies without a perioperative care context, surgical decisions or patient flow context were also excluded. Studies that compared only algorithms or looked into hospital expenses or cost control were excluded. Studies that concentrated on forecasting diseases or mortality from patient data, patient data modelling from history, population-based case-control, or follow-up were excluded, since they do not focus on developing AI systems in the perioperative patient flow. Papers that were reviews, non-accepted pre-prints, commentary, editorial, or did not have a full text available were also excluded. Finally, a closer reading was conducted to select those papers that fulfilled a list of pre-established requirements (n=89). These requirements resulted in a final list of inclusion and exclusion criteria, which are presented in the Table 3.

Table 3. Inclusion and exclusion criteria.

Inclusion criteria	-Focus on Patient flow AND -Focus on Artificial intelligence AND -Focus on Perioperative care
Exclusion Criteria	-Is a review article -Is a non-accepted pre-print -Is a commentary -Is an editorial -Not about AI -No real-world solution -No perioperative care context -No patient flow context -Only about expenses/cost control -Only algorithm comparison, no practical use -Forecasting diseases or mortality from patient data -Patient data modelling from history -Follow-up study -Population based case-control studies -No full text available -No user interface -No surgical decisions

3.4 Data extraction and synthesis

Okoli (2015) describes that in the data extraction phase reviewers carefully gather data from each manuscript, which will be used as the starting point for the synthesis phase. Using a data extraction form is recommended to gather the information needed to respond to the research questions (Okoli, 2015; Kitchenham & Charters, 2007).

In this SLR, data was collected from the all the 89 articles and categorized. A data extraction Excel spreadsheet was created to help collect general information from articles and answer the research question. The approach of this review was to take into account a number of useful details with the potential for relevant data or retrieve appropriate information from the original studies. The data extracted from each paper is elaborated in Appendix C. The most significant data from the primary studies, which was gathered and used to compose the results, is described in Appendix D. In addition to data extraction, classification of the articles by research topics and keywords was useful in this step. Data synthesis was aided by this method.

Kitchenham and Charters (2007) explain that data synthesis consists of collating and summarizing the results of included studies. They state that synthesis can be descriptive and narrative, which means tabulating extracted information of studies in a way that is consistent with the research question (Kitchenham & Charters, 2007). According to Xiao and Watson (2019), data can be organized in varying ways, depending on the study; it can consist of a mix of graphs, tables, and written description. Okoli (2015) explain that the record which is gathered from each study is used to create the synthesis.

Articles were screened for relevancy using the predefined inclusion criteria (Table 3). In this step, after heading and abstract screening were accomplished, 89 articles were identified, and those 89 articles were assessed for their content and quality based on the full text. The full text of ten papers was not found, and these papers were thus excluded. We used an evaluating technique where three independent evaluators (Karin Väyrynen, Janne Liisanantti, Anne Huotari) evaluated the following aspects:

- Does the article report on a real-life system that is tested/developed with (historical) patient data?
    - Yes: Article describes clearly the real-life system with some user interface which is tested or developed.
    - No: Article does not report of any real-life system which is tested or developed.
    - Maybe: No clarity whether an user interface is developed or tested.
- Does the article report on a real-life use of AI system in patient flow management?
    - Yes: Article describes clearly a real-life AI system.
    - No: Article does not report a real-life AI system.
    - Maybe: No clarity whether an AI system is developed or tested.
- Does the article report of a real-life system that has reference to perioperative care? Yes/No/Maybe.

The goal of the evaluation was to find articles in which a real-life system with a user interface is studied. The purpose was to exclude studies that only focus on developing algorithms or comparing the applicability of different algorithms. The user interface itself was not the object of interest, but for the article to be included and the system to be reported on, the development had to be at a stage where a user interface exists.

Everyone did an independent evaluation first. Then we compared evaluations and discussed those articles we disagreed upon until we arrived at a classification that all three evaluators agreed with. After the evaluation process, 34 studies were selected for the final work, and the data of those studies was comprehensively studied and summarized, and the data extraction spreadsheet was further elaborated. After this phase, the author was able to categorize the remaining studies, and the quality of categorization was assessed together with the supervisors. According to Okoli (2015), reviewers must combine the papers they have already reviewed, chosen, and evaluated for their review in order to make sense of the papers as a whole. Okoli (2015) adds that the reviewers now compile, talk about, organize, and compare the papers.

The challenge in interpreting data extraction in this SLR arose from the fact that different studies had very different information about the systems that had been studied or developed. Some studies for example indicated clearly the perioperative context for the solution, but some of them did not. The benefits or challenges of using AI were not reported in many studies. Each system focused on different types of clinical tasks in different perioperative phases and patient conditions. The systems also did not have many similarities in terms of tasks and functionalities.

The primary studies that were selected for the review were categorized in the new spreadsheet according to the functionalities of clinical tasks each system had. In this phase, we used the same technique as earlier: three independent evaluators (Karin Väyrynen, Janne Liisanantti, Anne Huotari) evaluated the categorization of each study. The categorization was conducted based on the article “Development and evaluation of a comprehensive clinical decision support taxonomy: comparison of front-end tools in commercial and internally developed electronic health record systems” written by Wright et al. (2011). They carried out a survey for commercial EHR vendors and healthcare institutions in the USA. Based on the answers from seven vendors and four institutions, Wright et al. (2011) developed a comprehensive taxonomy and survey of the types of the front end CDS tools in use at that time. The present study was able to utilize the categorization of expert systems based on Wright et al. (2011). The expert systems categories had similar features in both Wright et al. (2011) and the primary studies of the present SLR. The process of analysing the studies to place them into the categories developed by Wright et al. (2011) was quite lengthy and required much discussion between myself, Karin and Janne. This was because the description of the purpose of the tool was in some cases quite minimal in the primary studies. This was because the intended purpose of a tool was in some cases not described in much detail. The subcategory "prognostic tools" in particular required careful reflection, and in the end we decided to include in this subcategory only those tools that gave some prognosis related to mortality (instead of prognosing other outcomes of disease), as Wright et al. (2011) had defined "prognostic tools" to predict mortality. Classifying the tools required analysing various pieces of information in different sections of the primary studies. All the primary studies fell under the Wright et al.(2011) categories (see Table 4) of "expert systems" or "workflow support", but none could be classified to into the categories of "medication dosing support", "order facilitators", "point-of-care alerts/reminders" or "relevant information display".

Table 4 describes the CDS taxonomy capabilities found in the commercial and internally developed systems which Wright et al. (2011) studied. Regarding workflow support, it was necessary to create a new categorization based on the primary studies, as the characteristics were different than those in the categorization Wright et al. (2011) described in their study.

Table 4. Categories of CDS systems, based on Wright et al. (2011).

Decision support system category	**Features**
Medication dosing support (Wright et al., 2011, p. 234)	Medication dose adjustment, formulary checking, single dose range checking, maximum daily dose checking, maximum lifetime dose checking, default doses/pick lists, indication-based dosing
Order facilitators (Wright et al., 2011, p. 235)	Medication order sentences, subsequent or corollary orders, indication-based ordering, service-specific order sets, condition-specific order sets, procedure-specific order sets, condition-specific treatment protocol, transfer order set, non-medication order sentences
Point-of-care alerts/reminders (Wright et al., 2011, p. 236)	Drug-condition interaction checking, drug-drug interaction checking, drug-allergy interaction checking, plan of care alerts, critical laboratory value checking, duplicate order checking, care reminders, look-alike/sound-alike medication warnings, ticklers, problem list management, radiology ordering support, intravenous (IV)/per os (PO) conversion, high-risk state monitoring, polypharmacy alerts
Relevant information display (Wright et al., 2011, p. 237)	context-sensitive information retrieval, patient-specific relevant data displays, medication/test cost display, tall man lettering, context-sensitive user interface
Expert systems (Wright et al., 2011, p. 238)	Antibiotic ordering support, ventilator support, diagnostic support, risk assessment tools, prognostic tools, transfusion support, nutrition ordering tools, laboratory test interpretation, treatment planning, triage tools, syndromic surveillance

Workflow support (Wright et al., 2011, p. 239)	Order routing, registry functions, medication reconciliation, automatic order termination, order approvals, free-text order parsing, documentation aids

During the categorization process, one more study was excluded from the review because it did not concentrate on the perioperative process. A total of 33 articles was included in the end, and each article had been carefully evaluated in the data extraction spreadsheet and in the second spreadsheet where all studies were further categorized. According to Okoli (2015), reviewers should have a polished, finished synthesis of the information at the end of this phase, and they should be able to compose the review relatively simply. Appendix E contains a list of all the studies that were included in this SLR. The search process of this SLR is summarized in Figure 4.

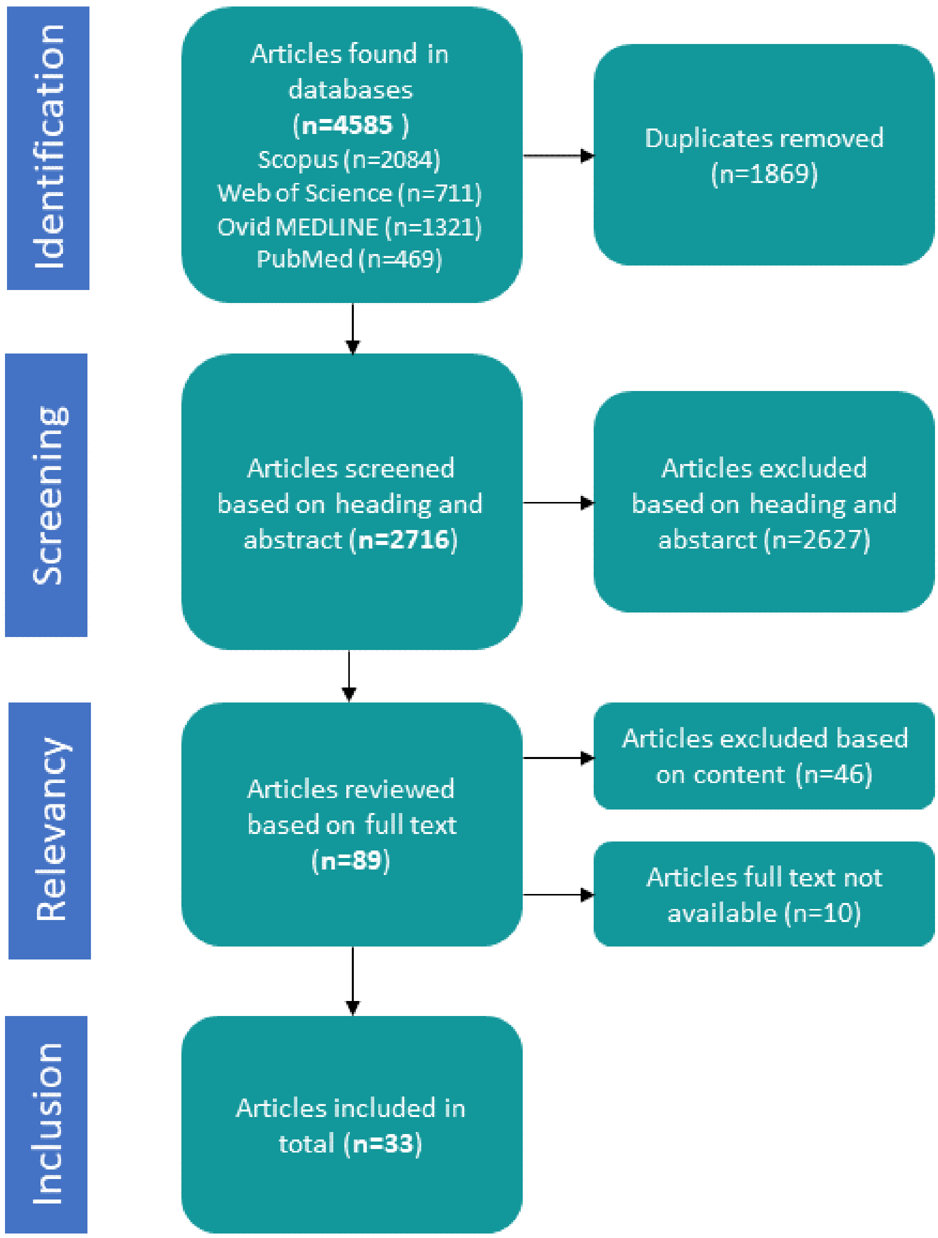

Figure 4. Literature review search process

3.5 Assessing quality

According to Okoli (2015), reviewers must grade studies based on how closely they follow various quality standards, as all primary research is not created equal. This quality assessment serves two connected but separate goals: to prioritize papers in order of quality and to exclude those publications that are deemed useless due to poor methodological quality (Okoli 2015). For confirming the quality of all the articles included in the study, quality assessment criteria can be applied (Kitchenham & Charters, 2007). According to Kitchenham and Charters (2007), quality assessment can, for example, be checklists of criteria that must be evaluated for each study.

Due to the relatively small number of studies included in this review, we decided to include all studies which fulfilled the inclusion criteria of focusing on patient flow, on AI, and on perioperative care. The nature of this study was finding the state-of-the art in the industry. As a result, we also wanted to include early test results and proofs-of-concept for AI applications that have been somehow integrated into the perioperative patient flow. Thus, an independent quality assessment was not conducted. As many of the systems were still on the proof-of-concept level or based on test data, results cannot be generalized in real life.

3.6 Reporting findings

The final stage of an SLR is reporting the results of the review. In this stage, the results are presented in writing and provided to the interested parties (Kitchenham & Charters, 2007). After data synthesis and the categorization of our findings, the results were composed based on the University of Oulu Master's thesis guidelines. The completed version of this study was published in Laturi, the library system in the University of Oulu. Chapter 4 presents the findings of the SLR.

3.7 Reliability and validity of the study

The author's lack of background in medicine poses challenge to the validity of the present study. However, by consulting Janne Liisanantti from the Research Unit of Translational Medicine, this constraint was reduced. The perioperative care and patient flow search terms were constructed together with Janne Liisanantti. A search string that was concise and balanced in accordance with the goals of the study was chosen. A pilot search was then executed first. Based on the results it produced, search phrases were modified and added. All search terms were reviewed and validated together with supervisors Janne Liisanantti and Karin Väyrynen.

89 articles were assessed for their content and quality based on the full text. We used an evaluating technique where three independent evaluators (Karin Väyrynen, Janne Liisanantti, Anne Huotari) evaluated studies based on the aspects we agreed together. 34 studies were selected for the final work and then categories by the author. The categorization of primary studies was based on the study of Wright et al. (2011) on CDS taxonomy. Finally, the primary studies were categorized according to the functionalities of clinical tasks each system had. In this stage, the same technique was used by three independent evaluators (Karin Väyrynen, Janne Liisanantti, Anne Huotari). The quality of the categorization of the primary studies was assessed together with supervisors, and a total of 33 articles were included in the end.

4. Results

In this chapter, the main findings of the present SLR are presented based on the included 33 primary studies on AI use in perioperative care. The functionalities of some of the solutions in this SLR are categorized in accordance with the Wright et al. (2011) publication "Development and evaluation of a comprehensive clinical decision support taxonomy: comparison of front-end tools in commercial and internally developed electronic health record systems". The solutions in this SLR were divided into two main categories of CDS systems: 1.) Expert systems, whose categorization was based on Wright et al. (2011). 2.) Workflow support, whose categorization was built in this SLR. All studies referred to in this section are the 33 primary studies (see also Appendix E), with the exception of reference to Wright (2011), which was utilized as a lens for categorizing primary studies.

Chapter 4.1 presents descriptive statistics about the primary studies generally. Chapter 4.2 presents clinical task characteristics of expert systems and workflow support found in the included studies. A high-level summary and reasoning of the findings is provided.

Chapters 4.3 Expert systems and 4.4 Workflow support define results based on the categorization of our papers. The subcategories recognized in this review were risk assessment tools, treatment planning, diagnostic support, prognostic tools, transfusion support, surgical workflow detection, operating room scheduling, bed management, and automation of clinical processes. Chapter 4.3 describes results from the expert systems and its subsystems in detail. In Chapter 4.4, all the results regarding workflow support and its subcategories are described.

Chapter 4.5 summarizes the CDS categories of expert systems and workflow support, and their subcategories which were found in the primary studies of the present SLR. Chapter 4.6 discusses the patient flow features and the interventions in AI applications of the primary studies. A summary of the future research suggestions and other improvement suggestions on developed applications found in the primary studies is presented in Chapter 4.7.

4.1 Descriptive statistics about primary studies

The quantity of different AI techniques which were found in the primary studies is presented in Figure 5. Among the 33 studies, the most popular AI technique was ML. Altogether 28 (85 %) solutions had an ML technique in their algorithms. Oher AI techniques were NLP (n=3), rule or case-based reasoning (CBR) (n=4), fuzzy logic (n=1), CV (n=1), and artificial neural network (ANN) (n=1).

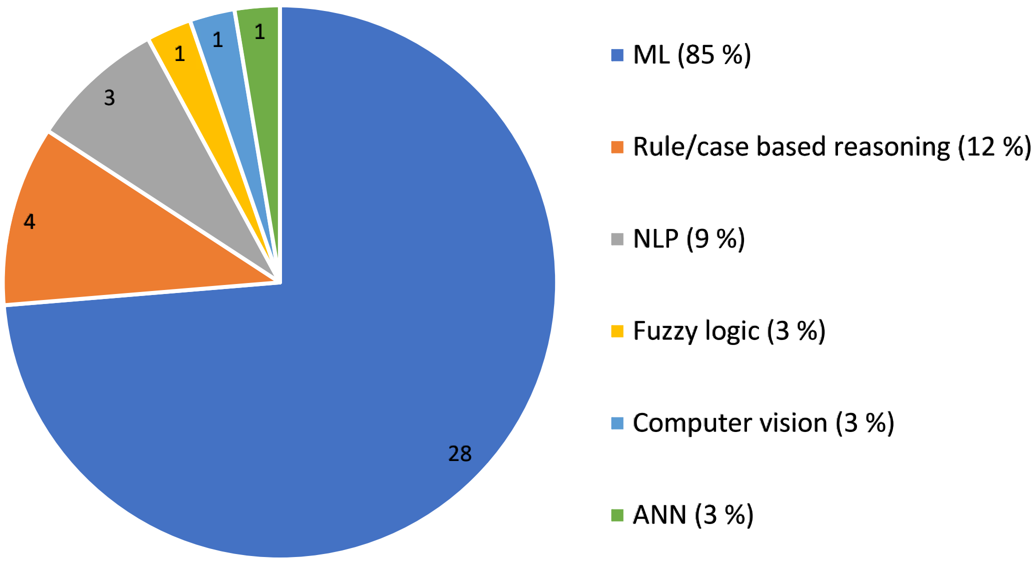

Figure 5. AI techniques and quantities in primary studies.

Additionally, the included AI applications were discovered to mainly provide decision support in the following categories of clinical tasks: risk assessment tools (n=11), treatment planning (n=9), workflow support (n=8), diagnostic tools (n=5), prognostic tools (n=3), transfusion support (n=1). Among the studies, three solutions had two main clinical tasks, while most of the solutions had one main task.

Further, the AI applications in 23 (70 %) studies targeted one or more specific diseases and conditions. The most prevalent disease or condition was cancer (n=7). Ten of the studies did not concentrate on any specific disease or condition. The primary studies which did not address any specific disease or condition had functionalities such as risk assessment, perioperative workflow, situation awareness, or planning.

Table 5 summarizes the countries in which the studies were conducted or the applications developed. The majority of the primary studies included in the SLR focused on the US: it was the origin of 14 solutions in total. 13 studies in total originated in the area of the European Union. China was the site of two of the primary studies. In South Korea, Brazil and New Zealand each, one primary study was found in this SLR. One of the studies published in US also had research cooperation with UK researchers. One of the primary studies was accomplished together with Italian and Polish researchers.

Table 5. Frequency of the primary studies by country.

Country	Frequency	Primary study
US	14	Bar et al. (2020), Bertsimas et al. (2018), Bishara et al. (2021), Brennan et al. (2019), Cole et al. (2021), Corey et al. (2018), Dantes et al. (2018), Datta et al. (2020), Fairley et al. (2019), Jordan and Rose (2010), Modaresnezhad et al. (2019), Murphree et al. (2015), Perkins et al. (2020), Pierce et al. (2020)
Portugal	4	Ferreira et al. (2019), Gonçalves et al. (2021), Oliveira et al. (2013), Sperandio et al. (2013)

China	2	Aikemu et al. (2021), Lv et al. (2021)
Norway	2	Babic et al. (2014), Berge et al. (2017)
Italy	2	Ciofi Degli Atti et al. (2020), Navarese et al. (2021)
(South) Korea	2	Hur et al. (2020), Yun et al. (2021)
New Zealand	1	Baig et al. (2012)
Spain	1	El-Fakdi and Gamero (2014)
Brazil	1	da Silveira Grübler et al. (2018)
Netherlands	1	Guédon et al. (2016)
Finland	1	Isoviita et al. (2019)
Poland	1	Navarese et al. (2021)
UK	1	Perkins et al. (2020)
Iran	1	Shabaniyan et al. (2019)
India	1	Somashekhar et al. (2018)

The research publication years were between 2010 and 2021. A few primary studies were found from the early 2010s. The number of studies related to the topic has increased until 2021. Figure 6 describes the distribution of primary studies for different years.

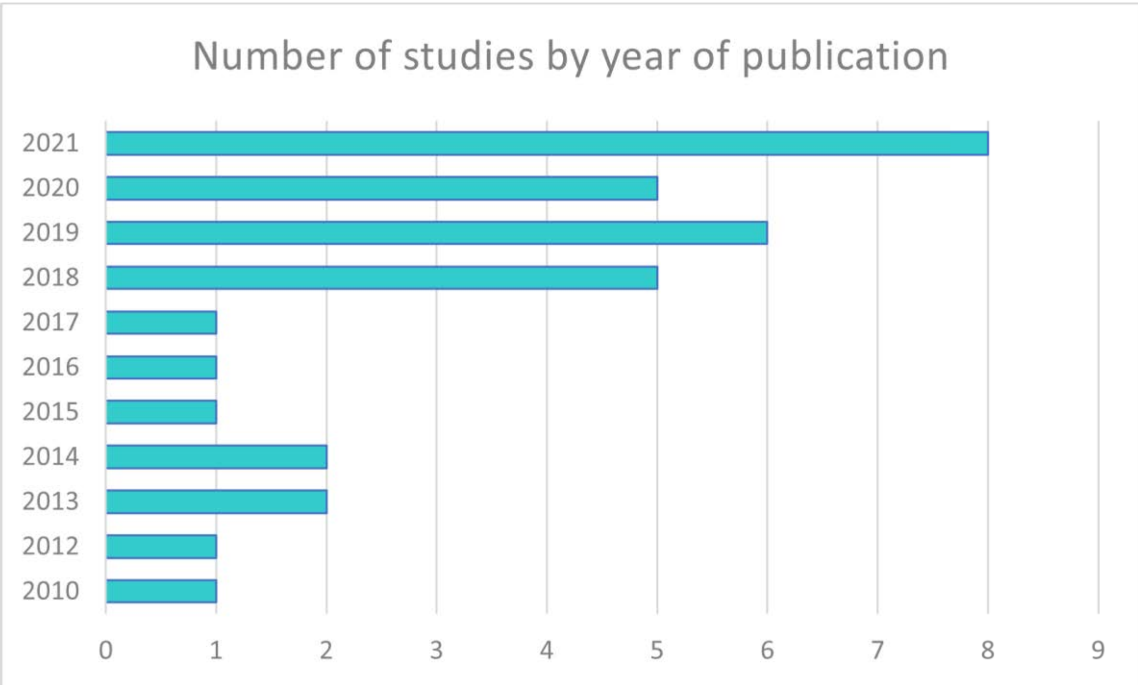

Figure 6. Distribution of primary studies by year.

Research methods in the primary studies are presented in Table 6. All primary studies investigate an application either developed by themselves or already developed earlier. The majority of the studies used systems development research or case study approaches for their research. Other used methodologies were retrospective studies, prospective studies, mixed-method researches, qualitative comparative analysis, empirical research and experimental study.

Table 6. Research methods in the primary studies

Research method	Primary study
Systems development research	Babic et al. (2014), Baig et al. (2012), Berge et al. (2017), Bertsimas et al. (2018), Fairley et al. (2019), Modaresnezhad et al. (2019), Murphree et al. (2015), Navarese et al. (2021), Perkins et al. (2020), Shabaniyan et al. (2019)
Case study	Bishara et al. (2021), Dantes et al. (2018), El-Fakdi and Gamero (2014), Ferreira et al. (2019), da Silveira Grübler et al. (2018), Guédon et al. (2016), Hur et al. (2020), Isoviita et al. (2019), Sperandio et al. (2013)
Retrospective study	Cole et al. (2021), Corey et al. (2018), Datta et al. (2020), Pierce et al. (2020), Somashekhar et al. (2018), Yun et al. (2021)
Prospective study	Aikemu et al. (2021), Brennan et al. (2019), Gonçalves et al. (2021)
Mixed-method research	Bar et al. (2020), Jordan and Rose (2010)
Qualitative comparative analysis	Ciofi Degli Atti et al. (2020)
Empirical research	Lv et al. (2021)
Experimental study	Oliveira et al. (2013)

The following chapter 4.2 presents the clinical tasks of CDS systems based on the categorizing of CDS taxonomy by Wright et al. (2011). After that, the workflow support tools categorization that was composed based on the studies in this review is introduced.

4.2 Clinical tasks of CDS systems

Studies in this review were categorized by the functionalities of clinical tasks each system had. The categorizing of studies is based on the Wright et al. (2011) clinical decision support taxonomy. They carried out a survey for commercial EHR vendors and healthcare institutions in the USA. Based on the answers from seven vendors and four institutions, Wright et al. (2011) developed a comprehensive taxonomy and survey of the types of the front end CDS tools in use at that time.

Some of the functionalities of the solutions in the primary studies which this SLR has discovered are based on the taxonomy of CDS tools by Wright et al. (2011). The solutions of these studies were categorized as expert systems, and their subsystems are presented in Section 4.2.1 and summarized in Table 7. All functionalities of the primary studies did not correspond to the taxonomy of CDS tools by Wright et al. (2011). These form the category of workflow support, and its subsystems are presented in Section 4.2.2 and summarized in Table 8.

4.2.1 Expert systems based on the Wright et al. (2011)

The majority of the studies included characteristics from expert systems included in the CDS taxonomy by Wright et al. (2011), and those subsystem categories are presented in

Table 7. Expert systems subcategories found in primary studies are diagnostic support, risk assessment tools, prognostic tools, treatment planning and transfusion support.

Table 7. Expert systems category's subsystems (adapted from Wright et al., 2011, p. 238, Table 7).

Subcategory	**Expert system subcategory description**	**Example**
Diagnostic support (Wright et al., 2011)	Differential diagnosis suggestions based on patient signs and symptoms (eg, Isabel, DxPlain, QMR).	Suggest a differential diagnosis of appendicitis, diverticulitis/osis, or kidney stones in patients with lower abdominal pain.
Risk assessment Tools (Wright et al., 2011)	Tools and calculators to estimate disease risks based on patient characteristics.	Calculate 10-year cardiovascular disease risk for a patient based on the Framingham risk score.
Prognostic tools (Wright et al., 2011)	Tools to estimate the survival of patients with cancer or other potentially life-limiting conditions based on diagnostic criteria and procedures performed.	Estimate survival for cancer patients based on tumor type, location, staging, and procedures performed.
Treatment planning (Wright et al., 2011)	Computer tools to assist in the planning of interventional procedures (ie, surgery or radiation therapy).	An image-guided treatment planning system used for radiation Oncology.
Transfusion support (Wright et al., 2011)	Recommendations regarding the appropriateness of transfusions and suggested products and dosing based on clinical indications.	Suggest fresh frozen plasma for patients with a high INR and taking warfarin.

Workflow support categorization, which was not found from the Wright et al. (2011) CDS taxonomy but was formed in this study, is presented in the following chapter. Workflow support has the subcategories surgical workflow detection, OR scheduling, bed management, and automation of clinical processes.

4.2.2 Workflow support systems based on new categorization

Eight studies had characteristics which were not found in the Wright et al. (2011) CDS categorization. These were categorized as workflow support systems, and that categorization was not based on the workflow tools which Wright et al. (2011) described, because of the differences in manifestation. The differences were as follows: the Wright et al. (2011) description of workflow support included order routing, registry functions, medication reconciliation, automatic order termination, order approvals, free-text order parsing and documentation aids. The categorization of workflow support formed in the present SLR includes surgical workflow detection, operating room scheduling, bed management and automation of clinical processes. Workflow support tools categorization is composed based on the characteristics of tools found in the primary studies of this review, and it is described in Table 8.

Table 8. Workflow support category and its subsystems, formed based on workflow solutions found in the present SLR.

Subcategory	Workflow support subcategory description	Example
Surgical workflow detection	Detects surgical phases	Computer vision in the surgical workflow phase detection
Operating room scheduling	Schedulers for optimizing patient flow in OR and PACU	Operating room optimization and scheduling, reducing PACU overcrowding, estimating time of surgery
Bed management	Situation awareness in bed management	Situation awareness as the basis for decision-making in bed allocation with elective patients or scheduled treatment, or in the case of discharging patient from the hospital
Automation of clinical processes	System for automatic transmission of data from the OR to the ICU in real time	Detecting abnormal events during surgery and identifying critical information to provide responsible care for patients arriving in the ICU

The following Chapter 4.3 elaborates on the expert systems categorization and its subcategories risk assessment tools, treatment planning, diagnostic support, prognostic tools and transfusion support.

4.3 Expert systems

This chapter introduces expert systems based on the categorization of Wright et al. (2011). Altogether 28 primary studies contained characteristics of five subcategories of expert systems: risk assessment tools, treatment planning, diagnostic support, prognostic tools and transfusion support. This chapter specifies for each subcategory the applications that have been implemented, the AI techniques used, the clinical task they have and the perioperative domain in which they are used. The perioperative domain is estimated based on the context in which each system is used. According to Erdogan and Denton (2011), the preoperative stage involves preparation for surgery, including possible pre-visit to a preoperative clinic, and the decision to have surgery. The intraoperative stage includes positioning the patient on the OR bed, anesthesia administration, and surgery (Erdogan & Denton, 2011). Finally, the postoperative stage begins with admitting the patient to the PACU or ICU followed by dischargement, and includes follow-up visits in the outpatient clinic as needed (Erdogan & Denton, 2011).

Every study is presented in a table that presents applications by author, clinical tasks and the perioperative domain in which they are used. The more detailed findings of the primary studies which included expert systems subcategories are elaborated under each table.

4.3.1 Risk assessment tools

Most of the solutions in the studies were characterized as risk assessment tools; altogether 11 studies included features from these. This subcategory of expert systems consists of tools and calculators to estimate disease risks based on patient characteristics (Wright et al., 2011). All risk assessment probably aims at improving treatment planning, but if not explicitly mentioned that the system is used to somehow plan further treatment, then it is not classified as a treatment planning system.

Table 9 presents studies which had risk assessment tool features: the application, the AI technique which was studied, and the clinical tasks the solution has. Additionally, the perioperative domain is categorized. Risk assessment tools were used in various perioperative stages. All of the tools utilized ML as an AI technique.

Table 9. Risk assessment applications and clinical tasks.

Author (year)	**Application**	**AI technique**	**Clinical tasks**	**Perioperative domain**
Bertsimas et al. (2018)	Surgery risk calculator POTTER, online and phone application	ML	Emergency surgery risk calculator.	Preoperative
Bishara et al. (2021)	Opal, Anesthesia information management system (AIMS)-based ML system created for clinical and research operations	ML	Clinical decision support in anesthesia. Pre-operative prediction of post-operative acute kidney injury.	Postoperative, intraoperative
Brennan et al. (2019)	MySurgeryRisk algorithm for preoperative risk assessment	ML	Estimating preoperative risk.	Preoperative
Cole et al. (2021)	A clinical decision support tool	ML	Predicting fascial dehiscence after exploratory laparotomy. Calculates net clinical benefit. Can be used at the point of care.	Perioperative, intraoperative, postoperative
Gonçalves et al. (2021)	Web-based tool to facilitate the usability of the selected models	ML	Surgical risk prediction of cancer patients.	Postoperative
Corey et al. (2018)	Decision support tool, Pythia risk calculator	ML	An online calculator requiring input of 9 data fields to produce a risk assessment within the clinic environment. Predicting postoperative complication risk.	Preoperative, postoperative
Datta et al. (2020)	MySurgeryRisk PostOp platform	ML	Predicting 7 postoperative complications (ICU length of stay >48 h, mechanical ventilation >48 h, neurologic complications including delirium, cardiovascular complications, acute kidney injury, venous thromboembolism and wound complications).	Intraoperative, postoperative

Murphree et al. (2015)	Prototype: integration of adverse transfusion event prediction models running in R into a recently developed CDS and alerting system	ML	Preventing adverse reactions by avoiding risky transfusions, or else to mitigate the consequences of an adverse reaction by identifying high-risk patients for increased post-transfusion observation.	Perioperative, intraoperative, postoperative
Navarese et al. (2021)	PREDICT-TAVR: Predictive model / risk model / 6-item nomogram tool and a web-based calculator	ML, random forest, naïve Bayes, logistic regression classifiers	Helping with decision-making and event prevention by identifying patients who are at risk of bleeding after transcatheter aortic valve replacement.	Postoperative
Perkins et al. (2020)	Website for clinicians to apply their model	ML, Bayesian network	Predicting outcomes following lower extremity revasculari-zation in trauma patients.	Postoperative
Pierce et al. (2021)	ACS-NSQIP risk calculator	ML	Predicting surgical risk in patients undergoing adult spinal deformity corrective surgery. Preoperative patient optimization and helping to mitigate and reduce postoperative complications.	Preoperative

The more detailed findings of the primary studies which included risk assessment functionalities are described in the following summaries of every tool. Summaries include conclusions regarding the tool, possible challenges, and evaluations regarding the usability and how well the tool is adapted to its purpose, if the information is provided in the study report. Summaries have been created for each study, detailing the information discovered in each study report, if that information was provided in the primary study.

Bertsimas et al. (2018) designed surgery risk calculator POTTER for emergency surgery. It utilizes big data and ML algorithms and can be integrated into a EHR environment. Bertsimas et al. (2018) conclude that the calculator is very accurate and simple to use, and it has the ability to continuously enhance accuracy through continuing ML. According to Bertsimas et al. (2018), POTTER could be helpful as a tool in the preoperative bedside counseling of emergency surgery patients and families.

Bishara et al. (2021) studied Anesthesia information management system (AIMS) -based ML system Opal, which is designed specifically for large-scale ML. It is designed for pre-operative prediction of post-operative acute kidney injury. Opal offers unified connection between the EHR and healthcare professionals: it allows the utilization of running algorithms that use EHR data in real-time to inform and improve clinical care. It is a specific AIMS-based ML system created for clinical and research operations. Opal offers quick data extraction, flexible queries based on cohort selection defined by the supplier, and a detailed dashboard for thorough data visualization and ML algorithm application. According to Bishara et al. (2012), this all-encompassing strategy for clinical ML offers a consistent solution to the issues of data accessibility, provider usability, and security. It can extract large-scale datasets. Bishara et al. (2021) state that the system can draw sophisticated associations using a variety of features. Using dynamic cohort selection and data visualization approaches that improve user feedback and data clarity, the system bridges the gap between the provider and the algorithm, helping the user understand the algorithm and context. A challenge recognized regarding the ML system in Opal is inaccurate and missing EHR data; data accuracy cannot be guaranteed or missingness of EHR can't be avoided (Bishara et al., 2021). Another challenge is that some users may not have statistical knowledge or ML technique familiarity and there is a risk of misunderstanding results. Bishara et al. (2021) also mentions Opal's drawback in restricted generalizability and lack of compatibility in both data extraction and implementation.

Brennan et al. (2019) analyzed the MySurgeryRisk algorithm's usefulness and precision for preoperative risk assessment. They compared the accuracy of perioperative risk assessment between physicians and MySurgeryRisk. MySurgery is an algorithm for preoperative risk assessments that help clinicians learn information and enhance their risk assessment ability. 20 surgical intensivists were asked to utilize and evaluate MySurgeryRisk in a clinical workflow simulation to estimate preoperative risk. The results of Brennan et al. (2019) show that the algorithm is practical and well-accepted by doctors and can be implemented for real-time predictive analytics using data from the EHR: most respondents said MySurgeryRisk was helpful and simple to use, and they thought it would be beneficial in decision-making. The design and deployment of this system will require the early involvement of physicians as important stakeholders, which is essential to its success.

Cole et al. (2021) aimed to develop a model that could predict fascial dehiscence after exploratory laparotomy. The patient flow aspect in the study was guiding clinical decisions at the point of care. According to Cole et al. (2021), risk factors were identifiable either before or during surgery, allowing the tool to be used at the point of care. They concluded that the model might improve surgeons' point-of-care decision-making by improving patient risk assessment for fascial dehiscence during the perioperative phase. The tool calculates net clinical benefit and can be used at the point of care (Cole et al., 2021).

The patient flow aspect in the study of Gonçalves et al. (2021) was the use of ML techniques in the surgical risk prediction of cancer patients. They investigated how postoperative complications can be predicted based on ML. Models for ML created using their single-center cohort were able to enhance the precision of an earlier traditional risk score. Gonçalves et al. (2021) developed for physicians a web-based clinical decision assistance tool that was created using only a few input variables. By providing new visualization options for tree-based models, model interpretability is also improved to facilitate medical decision-making. Additionally, data gathering procedures are made more efficient by the availability of information on essential variables for outcomes prediction. According to Gonçalves et al. (2021), their system has many potential challenges. Questions arise regarding missing values in the dataset, because single-center cohort is limited, which may cause difficulties in algorithm training, separate validation was made only for a limited set of patients and the tool was not tested with multi-center data.

Pythia risk calculator built by Corey et al. (2018) is an online calculator requiring input of nine data fields, the purpose of which is to produce a risk assessment within the clinic environment. According to Corey et al. (2018), Pythia is a "pipeline" of EHR / patient data as the basis of ML, and a web user interface based on which the patient's risks are scored. The solution can be used to identify high-risk surgical patients, and to locate patients for focused perioperative care. According to Corey et al. (2018), this tool performed better than both the ACS NSQIP calculator and heuristics created by clinical professionals to identify high-risk patients, offering a better method for doctors to predict postoperative risk for patients.

Datta et al. (2020) described a model that predicts postoperative complications considering intraoperative events. The patient flow aspect in the study of Datta et al. (2020) was that both the surgeon who performs an operation and the patient are better informed when postoperative complications are predicted in the preoperative environment. This study utilized also intraoperative data and assumed that it will improve prediction. Datta et al. (2020) researched predicting seven postoperative complications (intensive care unit length of stay >48 h, mechanical ventilation >48 h, neurologic complications including delirium, cardiovascular complications, acute kidney injury, venous thromboembolism, and wound complications) considering intraoperative events. Their conclusion was that predicting all seven postoperative complications with ML models that used preoperative and intraoperative data showed higher accuracy, discrimination, and precision than models that just used preoperative data (Datta et al., 2020).

Murphree et al. (2015) concentrated on improving transfusion-related outcomes in the perioperative environment. Their system had characteristics of risk assessment tool and transfusion support. Their system aims to either prevent adverse reactions by avoiding transfusions that have a high risk of reaction, or to decrease the effects of a negative reaction by identifying high-risk patients who require more post-transfusion monitoring. It can fetch data from several data sources such as electronic medical records, sensor data which records physiological measurements, billing data, laboratory data and pharmacy history. The system of Murphree et al. (2015) is a prototype, running as an alpha release, meaning that only the development team is receiving alert.

Navarese et al. (2021) developed a system to identify patients at risk of bleeding post-transcatheter aortic valve replacement, which can assist in decision-making and event prevention. It utilizes basic clinical information. The result of the study was that PREDICT-TAVR is a useful, validated 6-item tool that can help with decision-making and event prevention by identifying patients who are at risk of bleeding after transcatheter aortic valve replacement.

Perkins et al. (2020) developed a ML algorithm to predict outcomes following lower extremity revascularization in trauma patients. They demonstrated in their research that limb viability and the expected result of limb revascularization can be accurately predicted using a Bayesian network from existing clinical data. The conclusion of Perkins et al. (2020) was that this knowledge could complement clinical judgment, support treatment choices, and help set reasonable treatment goals.

The tool developed by Pierce et al. (2020) predicts surgical risk in patients undergoing adult spinal deformity corrective surgery. The system predicts postoperative risk, and it is used for preoperative patient optimization and to reduce postoperative complications. In addition to risk assessment, this tool has functionalities of a prognostic tool. Patients having surgery for adult spinal deformity had their postoperative risks predicted using the ACS-NSQIP risk calculator developed by Pierce et al. (2020). According to the authors, this device can be used to optimize preoperative patient care and to decrease and prevent postoperative complications.

4.3.2 Treatment planning

The second largest group of studies were characterized as treatment planning solutions. Eight of the studies were categorized in this subcategory. According to Wright et al. (2011), the treatment planning category involves computer tools assisting in the planning of interventional procedures. In the primary studies of this SLR, treatment planning solutions consisted also of small individual procedures. AI categories that were utilized in this subcategory were ML, case-based reasoning, rule-based algorithms and rule-based semantic networks. Table 10 summarizes treatment planning functionalities found in this SLR.

Table 10. Treatment planning applications and clinical tasks.

Author (year)	Application	AI technique	Clinical tasks	Perioperative domain
Aikemu et al. (2021)	Watson for Oncology (WFO)	ML	Clinical adviser and a learning system in cancer treatment.	Preoperative, postoperative
Babic et al. (2014)	Web-based Clinical Decision Support System (CDSS)	ML, Case-based reasoning	Giving decision support and build estimates of the outcomes to the physicians.	Intraoperative
El-Fakdi & Gamero (2014)	Clinical decision support system eXiTCDSS	Case-based reasoning	Providing doctors with case-specific assessments during complex surgery or minimally invasive surgery.	Intraoperative
Jordan and Rose (2010)	Multimedia abstract generation of intensive care data (MAGIC)	Rule-based algorithms	Identifying unusual events during cardiac surgery.	Intraoperative, postoperative
Modaresnezhad et al. (2019)	RxSem system	Rule-based semantic networks and ML	Utilization of existing clinical data for improving patient outcomes, improving clinical decision making. Prediction of bariatric surgery outcomes.	Postoperative
Shabaniyan et al. (2019)	System to predict the postoperative outcome of kidney stone treatment procedures and to provide operational support	ML	Predicting surgical results, predicting whether a patient will need a stent after surgery, and predicting the need for blood transfusion.	Preoperative
Somashekhar et al. (2018)	Watson for Oncology, AI clinical decision-support system	ML	Making treatment decisions.	Preoperative
Yun et al. (2021)	Watson for Oncology	ML	Aiding doctors in treatment planning.	Preoperative

The contribution of the primary studies, which included treatment planning functionalities, is explored in greater depth here. Summaries include conclusions regarding the tool, possible challenges, and evaluations regarding the usability and how well the tool is adapted to its purpose, if the information is provided in the study report.

Aikemu et al. (2021) compared Watson for Oncology (WFO) suggestions to clinicians made in a preoperative and postoperative setting. Their study concentrated on cancer treatment (colorectal cancer) of patients who underwent surgery (intraoperative phase). They emphasized the validity and timeliness of clinical guidelines and other therapeutic information critical for cancer care. According to Aikemu et al. (2021), design of efficient evidence based DSS systems is still ongoing. Their results suggest that DSS needs validation and updates, as therapies and suggestions proceed. Aikemu et al. (2021) emphasize also that continuous training is essential for improving the capability of WFO. It is also necessary to evaluate elderly patients' health status and treatments because same standards cannot always be applied for them. Aikemu et al. (2021) emphasize localization, which is also an important aspect, as treatment recommendations and care vary in different counties. Aikemu et al. (2021) discovered the untapped potential of the self-learning machine and observed broad agreement by comparing the recommendations given by WFO, a decision support tool to provide individualized medical recommendations, and a skilled multidisciplinary oncology team. Aikemu et al. (2021) did not report on their study the AI technique which WFO utilizes, but author of this SLR classified it as a ML system.

The study of Aikemu et al. (2021) suggests that oncologists are better able to fulfil the promise of precision medicine when they use cancer decision-support systems. Also, Somashekhar et al. (2018) compared treatment agreement between the multidisciplinary tumor board (breast cancer) and WFO. According to them, the system has shown to be well-aligned with the treatments decided upon by a multidisciplinary tumour board. Similarly, Yun et al. (2021) summarize that the WFO is important for doctors as a support tool in recommending the appropriate treatment based on the patient's electronic medical records. According to Yun et al. (2012), it must, however, be used cautiously, as the WFO's suggested course of treatment for people with advanced thyroid cancer might not be the optimal one. Therefore, while choosing the course of treatment for patients with advanced thyroid cancer, the surgeon's judgment gets priority over WFO recommendations (Yun et al., 2012).

Babic et al. (2014) demonstrated in their evaluation the CBR engine's utility in a web based CDSS system. It gave users confidence in the ability of the methodology to provide them with relevant cases on which to build estimates of the outcomes (surgery success, morbidity, and mortality). According to Babic et al. (2014), there are many challenges in the system. The user's background and experience affect the clinical factors they choose to start the retrieval, which affects how well the CBR engine functions. Finding similar situations uses a process that is quite similar to a doctor's, picking just a few factors out of many and ranking them according to importance, as noted by Babic et al. (2014). According to the authors, it has been shown that when assessing a case, doctors from various backgrounds prefer to focus on different factors. Besides, the definition of mathematical similarity by the algorithm may not always correspond to medical similarity. -Regarding missing values, substituting a missing value for a mean value may not be a suitable approach. A value that is closer to the truth should be used to replace any missing values. (Babic et al., 2014.)

Study of El-Fakdi and Gamero (2014) presents a solution that is a workflow-based CDSS created to provide doctors with case-specific assessments during surgery or minimally invasive surgery. The solution of El-Fakdi and Gamero (2014) facilitates interaction with physicians in a user-friendly way. Its workflow structure offers high versatility allowing the clinicians to decide in which steps of the procedure they wish to receive support. The tasks and attributes selection can easily be saved/loaded into independent files for future use. The attributes which the system uses are acquired through various imaging system devices and some data from patient historic profile (patient’s pathologies, allergies or past interventions). El-Fakdi and Gamero (2014) study shows that although it has been designed to give support to a wide range of interventions, the eXiTCDSS has been initially applied to give support to transcatheter aortic valve implantation interventions. The tool has demonstrated its performance giving support in a transcatheter aortic valve implantation intervention procedure with good results. (El-Fakdi and Gamero, 2014.)

Jordan and Rose (2010) developed an operational system that can identify unusual events during cardiac surgery and can therefore classified as a workflow support system. The risk of medical errors caused by poor communication is extremely high in patients undergoing heart surgery during the perioperative period (Jordan & Rose, 2010).

Important information is lost or misunderstood as caregivers change shifts or surgery patients move to different location in the hospital, as noted by Jordan and Rose (2010). The quality of the handover for heart surgery patients going from the OR to ICU was improved using an AI platform. This aspect characterizes the study of Jordan and Rose (2010) also as a treatment planning system. The system collects information from patient written text and other raw medical data and gives a handover of patient’s intraoperative course to ICU before the patient arrival. The results of Jordan and Rose (2010) show that clinical process automation using AI approaches produces beneficial outcomes.

Modaresnezhad et al. (2019) studied a system that predicts bariatric surgery outcomes. The patient flow aspect was the utilization of existing clinical data for improving patient outcomes and improving clinical decision making. Data sources were information on the patients' demographics, preoperative, intraoperative and postoperative medical information and side effects and complications or adverse effects observed after surgery. According to Modaresnezhad et al. (2019), the amount of data and the time it took to execute the analysis were significantly reduced using the rule-based semantic technique for decreasing data dimensionality. Both the reduced and full models performed equally well. Modaresnezhad et al. (2019) state that one of the most significant conclusions of the study is the similarity between the data mining outputs following data reduction. The runtime and data amount of the simplified model were much lower than those of the complete model, but their predictive power was comparable. The limitation of the study was that the system is a proof of concept with a limited data set (Modaresnezhad et al., 2019).

According to Shabaniyan et al. (2019), creating a ML-based system can help urologists treat big kidney stones. Their system was designed to predict the postoperative outcome of a kidney stone treatment procedure, counseling before an operation. Variables the system utilized were patient history, kidney stone characteristics and laboratory features. In predicting surgical results, predicting whether a patient will need a stent after surgery, and predicting the need for blood transfusion, the accuracy of the model of Shabaniyan et al. (2019) was 94.8%, 85.2%, and 95%, respectively.

4.3.3 Diagnostic support

According to Wright et al. (2011), the diagnostic support category involves creating differential diagnosis suggestions based on patient signs and symptoms. The five systems which were included in this subcategory involve functionalities of diagnosing and detecting certain conditions. Table 11 summarizes the diagnostic support functionalities which were found in this SLR.

Regarding applications for diagnostic support, this subcategory of clinical tasks utilized a greater variety of AI techniques than other subcategories. Systems which analyze texts from patient narratives, clinical notes and other free texts utilized an NLP technique (Berge et al., 2017; Ciofi Degli Atti et al., 2020; Dantes et al., 2018). Baig et al. (2012) studied fuzzy logic monitoring system. Diagnostic support systems utilized ML in two of the primary studies (Berge et al., 2017; Dantes et al., 2018) together with NLP. In addition, Lv et al. (2021) used ML in 3D surgical simulation software.

Table 11. Diagnostic support applications and clinical tasks.

Author (year)	Application	AI technique	Clinical tasks	Perioperative domain
Baig et al. (2012)	Fuzzy logic monitoring system-2 (FLMS-2)	Fuzzy-logic	Diagnosing a hypovolaemia event in anaesthetized patients	Anaesthesia monitoring
Berge et al. (2017)	A clinical decision support system for identifying and classifying allergies of concern for anesthesia during surgery	NLP, ML	Detecting and presenting potentially critical patient allergy in patient narratives, clinical decision making	Intraoperative
Ciofi Degli Atti et al. (2020)	Surgical site infection surveillance system based on hospital unstructured clinical notes and text mining	NLP: text mining, pattern-matching algorithm	Detecting surgical site infections in children based on the application of regular expressions of unstructured clinical notes collected through different information systems.	Postoperative
Dantes et al. (2018)	IDEAL-X, information extraction system	NLP, ML	Identifying venous thromboembolism diagnosis directly from the free text of radiology reports in electronic medical record	Postoperative
Lv et al. (2021)	INCOOL3D precision surgery planning analysis system	ML	Helping surgeons in preoperative planning by precisely performing image reconstruction and volume computation. The development of precise liver resection is specifically aided by the clinical application of this program.	Preoperative

Here are summarized the findings of each primary study, how the authors describe the outcomes of their study, and application characteristics of diagnostic support tools. Summaries include conclusions regarding the tool, possible challenges, and evaluations regarding the usability and how well tool is adapted to its purpose, if the information is provided in the study report.

Baig et al. (2012) studied the applicability of fuzzy logic in detecting critical events during anaesthesia and to accurately diagnose a hypovolaemia event in anaesthetized patients. The study demonstrated that evidence-based expert diagnostic systems are capable of correctly diagnosing hypovolaemia events in anesthetized patients and may be helpful in assisting anaesthesiologists in making decisions. Baig et al. (2012) demonstrated that the suggested FLMS-2 outperforms similar systems currently on the market. The full validation of the system as a therapeutically valuable diagnostic alarm system will be confirmed after real-time testing. Baig et al. (2012) state that the developed prototype is prepared for testing in a real-world setting, while it might require additional features and refining before it is appropriate for frequent clinical use. The final conclusion of Baig et al. (2012) is that the overall results and comparison to other monitoring systems indicate that this system might be a clinically valuable tool.

Berge et al. (2017) developed a CDSS for identifying and classifying allergies of concern for anesthesia during surgery. The system can detect and present potentially critical patient allergy data with acceptable accuracy from the EHR. Berge et al. (2017) found that the processing speed is higher than would be possible for doctors to achieve by manually reading the patient’s report. The system supports doctors by improving clinical decision-making and improves patient safety during surgery. According to Berge et al. (2017), the results were promising, and discussions on the implementing of a decision support system were ongoing in the Norwegian Hospital Trust.

Ciofi Degli Atti et al. (2020) studied the feasibility of Surgical site infection surveillance system (SSI) based on hospital unstructured clinical notes and text mining. According to Ciofi Degli Atti et al. (2020), a text-searching algorithm is a viable case-finding technique for surgical site infections. It has the potential to significantly lessen the effort of traditional monitoring, which requires direct contact with all families.

Dantes et al. (2018) used IDEAL-X, a novel information extraction software system, to identify venous thromboembolism from electronic medical records free texts of radiology reports and evaluated its accuracy. The study of Dantes et al. (2018) revealed that with specificity above AHRQ PSI-12, the solution successfully detected VTE from radiology reports. IDEAL-X has the potential to enhance the identification and monitoring of several medical conditions from the free text of electronic medical records (Dantes et al., 2018).

Lv et al. (2021) developed INCOOL3D, a precision surgery planning analysis system for liver resection. They demonstrated that the virtual surgical capability of the 3D surgical simulation software can help surgeons in preoperative planning by precisely performing image reconstruction and volume computation. The development of precise liver resection is specifically aided by the clinical application of this program: Surgeons can precisely understand the complex anatomy of the liver before the surgery and simulate potential OR situations so that they can timely modify the surgical plan (Lv et al., 2021).

4.3.4 Prognostic tools

Wright et al. (2011, p. 238) describe prognostic tools as having the ability “to estimate the survival of patients with cancer or other potentially life-limiting conditions based on diagnostic criteria and procedures performed”. Prognostic tools in this study included preoperative and postoperative domain tasks. Three solutions were characterized as having prognostic tools functionalities. All prognostic tools utilized ML.

The systems which were included in this subsystem involve functionalities of analyzing and visualizing EHR data, helping in decision making, predicting surgical risk in surgery patients, preoperative patient optimization, and mitigation and reduction of postoperative complications. The characteristics of prognostic tools in this SLR are listed in the Table 12.

Table 12. Prognostic tools applications and clinical tasks.

Author (year)	Application	AI technique	Clinical tasks	Perioperative domain
Isoviita et al. (2019)	CLOBNET, cloud-based machine learning system	ML	Enables comprehensive analysis and visualization of structured EHR data. Predictions on the basis of EHR data	Preoperative
Oliveira et al. (2013)	The CDSS system, which is based on the records & knowledge of cancer patients	ML	Helping healthcare professionals in decision making during prognosis	Postoperative
Pierce et al. (2021)	ACS-NSQIP risk calculator	ML	Predicting surgical risk in patients undergoing adult spinal deformity corrective surgery. Preoperative patient optimization and helping to mitigate and reduce postoperative complications.	Preoperative

All summaries of the primary study findings included in the prognostic tools subcategory are described here. Summaries include conclusions regarding the tool, possible challenges, and evaluations regarding the usability and how well tool is adapted to its purpose, if the information is provided in the study report.

Isoviita et al. (2019) showed how CLOBNET, an open-source, agile computational infrastructure, allows to convert structured EHR data into practical clinical information. They used the system to forecast the therapy response in patients with high-grade, life-threatening ovarian cancer (Isoviita et al., 2019). System can be used in a multicenter context or simply customized for various data sets and clinical settings, reducing the security concerns and administrative burdens associated with the sharing of health data. The system can fetch and merge data from multiple sources; Isoviita et al. (2019) used EHR databases and research databases. The data is used for the training of ML, and the system offers predictive models for disease prognostics. The results of Isoviita et al. (2019) are based on a small data set, which limits their generalizability.

Oliveira et al. (2013) proposed a ML CDSS solution which helps healthcare professionals in decision-making during prognosis. Oliveira et al (2013) came into the conclusion that the system could provide an efficient treatment plan and solve post-surgery prognostic uncertainty, but it was still under development and needed further refinement.

The tool developed by Pierce et al. (2020) predicts surgical risk in patients undergoing adult spinal deformity corrective surgery. Patients having surgery for adult spinal deformity had their postoperative risks predicted using the ACS-NSQIP risk calculator developed by Pierce et al. (2020). According to the authors, this device can be used to optimize preoperative patient care and to decrease and prevent postoperative complications. In addition to the prognostic tool, this tool has functionalities of risk assessment and is included also in Chapter 4.3.1.

4.3.5 Transfusion support

Transfusion support tools was the least common subcategory of expert systems; only one of the primary studies had characteristics of transfusion support (Table 13). Transfusion support tools can give suggestions for products and doses regarding the appropriateness of transfusions (Wright et al., 2011). The prototype of Murphee et al. (2015) had characteristics both from the risk assessment tools and transfusion support, and it is presented also in Chapter 4.3.1.

Table 13. Transfusion support tools applications and clinical tasks.

Author (year)	Application	AI technique	Clinical tasks	Perioperative domain
Murphree et al. (2015)	Prototype: integration of adverse transfusion event prediction models running in R into a recently developed CDS and alerting system	ML	Preventing adverse reactions by avoiding risky transfusions, or else to mitigate the consequences of an adverse reaction by identifying high-risk patients for increased post-transfusion observation.	Preoperative, intraoperative, postoperative

Chapter 4.4 elaborates workflow support categorization which was built in this review and is based on the characteristics that were not found in the Wright et al. (2011) review. Subcategories of workflow support systems included surgical workflow detection, operating room scheduling, bed management and automation of clinical processes.

4.4 Workflow support

Workflow support defines results based on the categorization of our papers. The categorization was built in this SLR. As described earlier in Chapter 4.2, workflow support in primary studies was categorized into four subcategories: surgical workflow detection, operating room scheduling, bed management and automation of clinical processes. The eight studies which were identified as workflow supporting tools, had functionalities including surgical workflow recognition, OR scheduling, PACU overcrowding detection, estimating time of surgery and optimizing scheduling. Also, functionalities of situation awareness in bed management, scheduling optimal patient flow from the nursing department to the OR, predicting unplanned cardiac surgery and automation of clinical processes were found. There were many AI techniques used, including ML, CV, ANN and rule-based algorithms.

Table 14 summarizes all the studies which were characterized as workflow support tools in this SLR. Every study is presented in a table that presents applications by author, and perioperative domain in which they are used. The perioperative domain is estimated based on the context each system is used. More detailed findings of the primary studies which included expert systems subcategories are elaborated after Table 14, in chapters 4.4.1-4.4.4.

Table 14. Workflow support applications and clinical tasks.

Author (year)	Application	AI technique	Clinical tasks	Perioperative domain
Bar et al. (2020)	Surgical workflow phase detection system	ML (DL), computer vision	Surgical workflow detection	Intraoperative
Fairley et al. (2019)	Scheduling system, operating room schedulers	ML	Operating room optimization and scheduling, reducing PACU overcrowding	Intraoperative, postoperative
Ferreira et al. (2019)	Adaptive Business Intelligence (ABI) platform	ML	Decreasing unanticipated delays and an improvement in efficacy of the service, by reducing the shifts wasted	Preoperative, intraoperative
da Silveira Grübler et al. (2018)	Prototype: IMBEDS, a hospital bed allocation hybrid model based on situation awareness	ANN	Bed management, situation awareness as the basis for decision-making in bed allocation with elective patients or scheduled treatment, or in the case on discharging patient from the hospital	Preoperative, postoperative
Guédon et al. (2016)	Real-time and online prediction system	ML	Prediction system for remaining surgery times based on the data of surgical devices	Intraoperative
Hur, et al. (2020)	Interactive visualization system	ML, DL	Predicting unplanned cardiac surgery of patients undergoing coronary artery bypass grafting surgery after an emergency hospital admission and elevated troponin levels	Preoperative, postoperative
Jordan & Rose (2010)	Multimedia abstract generation of intensive care data (MAGIC)	Rule-based algorithms	Identifying unusual events during cardiac surgery	Intraoperative, postoperative
Sperandio et al. (2014)	Intelligent decision support system (DSS)	ML	Enhancing operating room efficiency and addressing the fragile surgical waiting lists situation	Preoperative, intraoperative

4.4.1 Surgical workflow detection

Surgical workflow detection can be categorized as a subsystem in workflow support CDS systems. This SLR included the study of Bar et al. (2020) in a surgical phase detecting purpose. They studied the possibility of utilizing DL and CV in surgical workflow phase detection. Bar et al. (2020) demonstrated that the performance of AI significantly improved as the video count of the input dataset was raised from 50 to 745 using the data set of 1243 videos. They evaluated surgical workflow detection and presented a DL system that accurately detects surgical phases and can be implemented in new medical centres. Bar et al. (2020) believe that their study advances CV-based research and applications for laparoscopic surgery to the point of incorporating AI systems into the regular surgical workflow, aiding in decision-making, and eventually enhancing surgeon experience and patient care. The limitation of this study was that the results are specific to laparoscopic cholecystectomy and may not be transferable to other surgeries, and although the dataset used captures high surgical variability, it still has a bias towards a single center.

4.4.2 Operating room scheduling

This SLR included five OR scheduling studies. These systems are schedulers for optimizing patient flow in OR and PACU. According to Fairley et al. (2019), the hospital can profit greatly from efficient administration and precise OR scheduling. Significant advantages may result from more efficient scheduling and management of operating rooms, as stated by Fairley et al. (2019). They note that after surgery, most of the patients are transferred to the PACU to recover from anesthesia. PACU is a bottleneck in many hospitals: patients must wait in the OR until there is space in the PACU if it has reached capacity, which can cause delays and even cancellations for following OR procedures (Fairley et al., 2019). Fairley et al. (2019) created a three-part surgical patient sequencing strategy to reduce the PACU overcrowding and resulting OR delays. In their research, the utilization of ML algorithm to predict the PACU time allowed to reduce total PACU holds by 76 %, resulting in considerable cost savings. The model of Fairley et al. (2019) was developed and tested for one hospital, but it is generalizable to other hospitals and surgical settings.

Also Ferreira et al. (2019) studied surgery scheduling in hospital ORs, and created an Adaptive Business Intelligence (ABI) platform. A real dataset containing data on surgeries and shifts from hospital was used as a proof on concept. Their findings were encouraging, making this strategy an effective and efficient ABI event scheduling platform that can be customized for any organization or institution that wants to schedule a sizable number of events. It may lead to a decrease in unanticipated delays and an improvement in the efficacy of the service, by reducing the shifts wasted. The challenge of the system of Ferreira et al. (2019) is that it should be tested with more complex and wider data. Sperandio et al. (2013) also created a system to enhance OR efficiency and to address the fragile surgical waiting lists situation. The findings of the experiment reveal considerable improvements, including better use of resources and a decrease in overtime and undertime.

Guédon et al. (2016) developed system for real-time prediction of procedure duration in laparoscopic cholecystectomies. In those procedures, the activation of the electrosurgical equipment was used to forecast automatically and objectively the remaining time with an acceptable degree of accuracy. Guédon et al. (2016) conclude that in order to accomplish optimal OR scheduling and optimal patient flow from the nursing department to the OR, it is a potential prediction method. According to authors, the system achieves appropriate OR scheduling and streamlines the patient flow from the nursing department to the OR by objectively predicting the remaining procedure duration.

4.4.3 Bed management

Situation awareness in bed management is categorised to be included in workflow systems in this SLR. One study, da Silveira Grübler et al. (2018), was found in this subcategory. They developed as a proof-of-concept a hospital bed allocation hybrid model based on situation awareness. The beds selected by the hospital manager and those indicated by the suggested model were 93.5% similar, according to the results of da Silveira Grübler et al. (2018).

The system of da Silveira Grübler et al. (2018) is a model that researchers suggested to be used to assign patients to beds. IMBEDS is a hybrid model that helps with bed selection by combining several methods to manage a waiting list of both planned and emergency patients (da Silveira Grübler et al., 2018). The perioperative context in the study of da Silveira Grübler et al. (2018) was situation awareness as the basis for decision-making in bed allocation with elective patients or scheduled treatment, or in the case of discharging patient from the hospital.

4.4.4 Automation of clinical processes

Automation of clinical processes can be for example a system for automatic transmission of data from the OR to the ICU in real time. Two of the primary studies were categorized in this subcategory.

Hur et al. (2020) focused on patients who followed a series of events as a high-risk group: patients undergoing coronary artery bypass grafting surgery after an emergency hospital admission and elevated troponin levels. The goal was to examine the probability of unplanned cardiac surgery. The system suggested by Hur et al. (2020) helps with the identification of patient groups based on a patient's pathway, labeling simplification, and exploratory evaluation of the modeling results. The results of Hur et al. (2020) show that the suggested solution can assist medical personnel in examining the various patient journeys. Hur et al. (2020) state that their solution facilitates testing various clinical hypotheses using big data in the medical field, with the help of ML and DL. The system offers a fresh and effective method for assessing clinical hypotheses that may be turned into forecasting models.

Jordan and Rose (2010) developed an operational system that can identify unusual events during cardiac surgery. Because the system has also treatment planning functionalities, it is presented more specifically in Chapter 4.3.2.

Chapter 4.5 summarizes the total number of the CDS subcategories from expert systems and workflow support systems found in this SLR.

4.5 Summary of CDS categories in the SLR

The CDS types and subcategories that were discovered in this SLR are listed in the Table 15. The total number of expert systems subcategories found in the primary studies was 27. Categorization of expert systems was based on the study of Wright et al. (2011). The risk assessment tools subcategory was found in 11 studies. Nine of the studies had treatment planning subcategory features. Four of the studies included features from diagnostic support category and three studies included prognostic tools features. One study had transfusion support tools functionalities.

Workflow support features based on the categorization made in this SLR were found in eight primary studies. Four of them included OR scheduling features. Two had functionalities from automation of clinical processes, one from surgical workflow detection and one from bed management.

Table 15. CDS categories and subcategories found from the SLR.

CDS categories	Subcategories	Primary studies
Expert systems	Risk assessment tools	Bertsimas et al. (2018), Bishara et al. (2021) Brennan et al. (2019), Cole et al. (2021), Gonçalves et al. (2021), Corey et al. (2018), Datta et al. (2020), Murphree et al. (2015), Navarese et al. (2021), Perkins et al. (2020), Pierce et al. (2021)
	Treatment planning	Aikemu et al. (2021), Babic et al. (2014), El-Fakdi & Gamero (2014) Jordan and Rose (2010) Modaresnezhad et al. (2019), Shabaniyan et al. (2019), Somashekhar et al. (2018), Yun et al. (2021)
	Diagnostic support	Berge et al. (2017), Ciofi Degli Atti et al. (2020), Dantes et al. (2018), Lv et al. (2021)
	Prognostic tools	Isoviita et al. (2019), Oliveira et al. (2013), Pierce et al. (2021)
	Transfusion support	Murphree et al. (2015)
Workflow support	Surgical workflow detection	Bar et al. (2020)
	Operating room scheduling	Fairley et al. (2019), Ferreira et al. (2019), Guédon et al. (2016), Sperandio et al. (2013)
	Bed management	da Silveira Grübler et al. (2018)
	Automation of clinical processes	Hur et al. (2020), Jordan & Rose (2010)

The following chapter considers how the patient flow management in AI applications is approached in the primary studies.

4.6 Patient flow features in the primary studies

All the AI applications and tools in this SLR's primary studies had some kind of patient flow aspect in their features. All solutions in this review were classified as CDS systems. CDS refers to the use of technology and relevant patient information to aid in medical decision-making and improve healthcare delivery (Sutton et al., 2020). The categorizing of studies in this SLR is based on a) Wright et al. (2011) clinical decision support taxonomy expert systems (risk assessment tools, treatment planning, diagnostic support, prognostic tools and transfusion support) and b) the categorization of workflow support formed in the present SLR (surgical workflow detection, OR scheduling, bed management, automation of clinical processes).

According to Nguyen et al. (2022), decision support is one of the health IS interventions that has an impact on the patient flow. Other interventions Nguyen et al. (2022) listed, and this SLR found from the primary studies, were patient tracking, bed management and discharge management. Other studies have found the following interventions and features, that are also handled in this SLR: precise classifiers that consider both patient features and surgical variables (Markazi-Moghaddam et al., 2020), forecast and respond to potential negative outcomes, intraoperative counselling (Mishra & Leng, 2021), detection of at-risk patients, early diagnosis of complications and well-timed and efficient treatment (Maheshwari et al., 2020), improving patient safety, prognosis and prevention of surgical complications (Bates et al., 2021), real-time risk assessment (Bose & Talmor, 2018).

This chapter summarizes the patient flow characteristics and AI categorization found in the primary studies. Patient flow characteristics and AI categorization is analyzed in the subcategory of expert systems. The patient flow characteristics of workflow support solutions and AI categorization is discussed under one heading.

4.6.1 Risk assessment tools

All 11 risk assessment tools utilized ML in their functionalities. In addition, two of the applications mentioned using of ML algorithms and techniques of random forest, naïve Bayes, logistic regression classifiers or bayesian network in their solutions. The following paragraphs discuss the patient flow features of the primary studies which had risk assessment tools classification.

Risk prediction in CDS systems is considered to help in patient flow. Bishara et al. (2021) studied the effectiveness of an anesthesia information management system (AIMS) - based ML system. Their CDS system offers preoperative prediction of post-operative acute kidney injury. Cole et al. (2021) developed a CDS tool that can help to guide clinical decisions at the point of care. The model might improve surgeons' point-of-care decision-making by improving patient risk assessment for fascial dehiscence during the perioperative phase (Cole et al., 2021). The system of Navarese et al. (2021) is a predictive model / risk model / 6-item nomogram tool and a web-based calculator. Their system helps with decision making and event prevention by identifying patients who are at risk of bleeding after transcatheter aortic valve replacement. Perkins et al. (2020) developed a system for predicting outcomes following lower extremity revascularization in trauma patients.

The following other risk assessment interventions were found: surgical risk prediction of cancer patients (Gonçalves et al., 2021), predicting postoperative complication risk (Corey et al., 2018), predicting postoperative complications (Datta et al., 2020), risk calculator for emergency surgery (Bertsimas et al., 2018) and for estimating preoperative risk (Brennan et al., 2019). Pierce et al. (2021) studied the efficiency of the system predicting surgical risk in patients undergoing adult spinal deformity corrective surgery. The patient flow aspect of the system in the study of Pierce et al. (2021) is preoperative patient optimization and helping to mitigate and reduce postoperative complications. The system of Murphree et al. (2015) prevents adverse reactions by avoiding transfusions that have a high risk of reaction and identifying high-risk patients who require more post-transfusion monitoring.

4.6.2 Treatment planning

AI categories that were utilized in the treatment planning systems were ML (n=6), CBR (n=2), rule-based algorithms (n=1) and rule-based semantic networks (n=1). All patient flow aspects of the eight studies are presented here.

Researchers who studied WFO's usability on decision support conclude that the treatment suggestions it draws are well aligned with the suggestions of clinicians. It can be concluded that WFO is important for doctors on recommending treatment based on the patient's EHR: it can support on decision making and helps in treatment planning (Aikemu et al., 2021; Somashekhar et al., 2018; Yun et al., 2021).

Also, other primary studies in the treatment planning category had CDSS functionalities on their scope. Babic et al. (2014) built web based CDSS that gives decision support and builds estimates of the outcomes to the physicians. System of El-Fakdi and Gamero (2014) provides doctors with workflow based CDSS with case-specific assessments during complex surgery or minimally invasive surgery. Jordan and Rose (2010) built a system which identifies unusual events during cardiac surgery, and it can recognize data that is essential for providing patients entering the ICU with responsible care. As a result, the system of Jordan and Rose (2010) enhances situational awareness, and they state that it proves that the automation of clinical processes with the help of AI can have positive impacts.

Modaresnezhad et al. (2019) built RxSem system for Prediction of bariatric surgery outcomes. The patient flow aspect is the utilization of existing clinical data for improving patient outcomes, and thus improving clinical decision making. The solution of Shabaniyan et al. (2019) was built to predict the postoperative outcome of kidney stone treatment procedures and to provide operational support.

4.6.3 Diagnostic support

AI categories used in the solutions of the five diagnostic support categories were fuzzy-logic (n=1), NLP (text mining) (n=3), pattern-matching algorithm (n=1) and ML (n=3). The patient flow functions of all five systems in this category are presented here.

The patient flow interventions of the diagnostic support systems were diagnosing a hypovolaemia event in anaesthetized patients (Baig et al., 2012), identifying and classifying allergies of concern for anesthesia during surgery (Berge et al., 2017), helping surgeons in preoperative planning by precisely performing image reconstruction and volume computation (Lv et al., 2021).

Ciofi Degli Atti et al. (2020) and Dantes et al. (2018) studied detection and surveillance of medical conditions from unstructured, free texts of EHR. According to Ciofi Degli Atti et al. (2020), these systems have the potential to reduce workload of traditional surveillance.

4.6.4 Prognostic tools and transfusion support

Both the prognostic tools and transfusion support solutions, altogether four studies, mentioned ML as an AI category used in their solutions. All of them had patient flow interventions or functionalities in their systems and they are presented here.

Isoviita et al. (2019) developed a system which enables comprehensive analysis and visualization of structured EHR data. It draws predictions based on EHR data (Isoviita et al., 2019). Other studies had interventions of helping healthcare professionals in decision-making during prognosis (Oliveira et al., 2013), preoperative patient optimization and helping to mitigate and reduce postoperative complications (Pierce et al., 2021) and preventing adverse reactions by avoiding risky transfusions, or else to mitigate the consequences of an adverse reaction by identifying high-risk patients for increased post-transfusion observation (Murphree et al., 2015).

4.6.5 Workflow support

AI techniques ML (DL) (n=6), CV (n=1), ANN (n=1) and rule-based algorithms (n=1) were found from the solutions on workflow support. Altogether eight studies were categorized as workflow support solutions.

Surgical workflow detection subcategory was found from only one of the primary studies. The patient flow aim of the system in the study of Bar et al. (2020) was to aid surgeons in their daily routine. Authors evaluated that their analysis could help future solutions adapt in the clinical decision-making process and improve patient care.

OR scheduling was categorized in this review as systems that are schedulers for optimizing patient flow in OR and PACU. Four of the studies included following features of patient flow: reducing the PACU overcrowding and resulting OR delays (Fairley et al., 2019), reducing the shifts wasted (Ferreira et al., 2019) and enhancing OR efficiency and addressing the fragile surgical waiting lists situation (Sperandio et al., 2013) and real-time prediction of procedure duration (Guédon et al., 2016).

Situation awareness in *bed management* system characteristics was found in one study. The patient flow feature in the study of da Silveira Grübler et al. (2018) was situation awareness as the basis for decision-making in bed allocation with elective patients or scheduled treatment, or in the case on discharging patient from the hospital.

Automation of clinical processes includes patient flow characteristics for automatic transmission of data between different wards, and two of the primary studies were classified in this group of workflow systems. The system of Hur et al. (2020) helps with the identification of patient groups based on a patient's pathway, labeling simplification, and exploratory evaluation of the modeling results. The system of Jordan and Rose (2010) can identify unusual events during cardiac surgery.

All the recommendations for further study and other improvement suggestions regarding the development of AI tools that were discovered in the primary studies are compiled in the Chapter 4.7.

4.7 Future suggestions found in the primary studies

Here are summarized some aspects which were highlighted in the studies which should be taken into account while developing AI tools in the future. This chapter analyses studies which had broader suggestions for the future development of AI tools. Some of the studies concentrated on improving the functionalities of their own applications. Those improvement suggestions are also analyzed in this review. Data is collected from the primary studies which had some suggestions for future research or other improvement suggestions.

4.7.1 Future research suggestions

Researchers suggest using their findings to improve the adoption of applications in clinical practice; there is a need for more diverse patient populations and demographics, treatment settings as well as multicenter settings and localization (Aikemu et al., 2021; Yun et al., 2021; Somashekhar et al., 2018; Gonçalves et al., 2021; Bishara et al., 2021; Dantes et al., 2018; Perkins et al, 2020). They also suggest potential applications for AI-powered support and highlight the need for further research in areas such as medical CBR systems, ML models for predicting clinical outcomes, risk calculators, and surgical phase detection (Babic et al., 2014; Bertsimas et al., 2019; Bar et al, 2020, Bishara et al., 2021, El-Fakdi & Gamero, 2014).

Further research is needed to evaluate the impact of DSS in clinical settings, for example the complexity of ML statistical approaches used in the study of Cole et al. (2021) makes them more challenging to understand and apply in clinical contexts. The retrospective nature of the study of Cole et al. (2021) limits the capture of all factors that may impact the risk of dehiscence, such as surgeon skill, perioperative medical management, or healthcare system factors. Their model was trained on relatively old data and needs to be refined with a new dataset (Cole et al., 2021). New developments are also being made to improve user interfaces, implement better default distance calculation methods, and expand risk calculators for surgical subspecialties (Pierce et al., 2021; El-Fakdi & Gamero, 2014).

Further research is needed also for developing ML models using EHR data to predict clinical outcomes in future patients and the implementation of more advanced ML techniques (Bishara et al., 2021). Ciofi Degli Atti et al. (2020) see as a future need for developing text-searching algorithms for the surveillance of other quality measures and stratification of risk factor rates associated with SSI development; validation of predictive scores of surgical site infections in children (Ciofi Degli Atti et al., 2020). Datta et al. (2020) suggest that future studies should use the models of their study in clinical settings and work to improve decision-making for patients with intermediate risk, who make up the majority of the population and present special problems for predictive analytics. There may be gaps and missing values in the patient data, and therefore some measurements can be biased (Berge et al., 2017; Babic et al., 2014; Gonçalves et al., 2021; Bishara et al., 2021; Bertsimas et al., 2019). Many studies concentrated only on one specific surgical procedure, and results are not generalizable to other procedures (Bar et al, 2020; Perkins et al, 2020).

Corey et al. (2018) study shows that using a large institution's EHR data for ML purposes can result in effective decision support tools for identifying high-risk patients and managing patient care. However, further research is needed to evaluate the impact of these tools in clinical settings and optimize the data flow for future ML efforts (Corey et al., 2018).

Hur et al. (2020) state that future work is expected to explore temporal information from increasing amounts of EHR data, evaluate the proposed architecture for other clinical use cases, review the attention model with better clinical interpretation, and construct a sustained continual learning environment using real-world data. Additionally, Hur et al. (2020) state that medical experts are needed to evaluate the qualitative aspects of pathway patterns based on the mining algorithm. Also, Brennan et al. (2019) suggest in their research that including doctors as early stakeholders both in the design and implementation of the technology will be essential.

Many studies identified problems caused by incomplete data. There may be gaps and missing values or variables in the patient data, and therefore some measurements can be biased (Berge et al., 2017; Babic et al., 2014; Gonçalves et al., 2021; Bishara et al., 2021; Bertsimas et al., 2019; Navarese et al., 2021).

4.7.2 Other improvement suggestions on developed applications

Some of the studies focused on enhancing the capabilities of the applications developed by the researchers themselves. Those suggestions are analyzed here. The future plans of Sperandio et al. (2013) are extending their DSS; the aim is to perform a better allocation of the different specialities to the OR and enhancing their optimization module and simulation component. The results of the study of Shabaniyan et al. (2019) on developed DSS are advised to be considered as a preliminary exercise; the authors state that system has the potential to be a useful tool for pre-operative counseling, predicting a surgical outcome and choosing a surgical treatment for removing kidney stones. Oliveira et al (2013) came into the conclusion that their CDSS system could provide an efficient treatment plan and solve post-surgery prognostic uncertainty, but it was still under development and needed further refinement and re-evaluating algorithms with new variables. The system of Murphree et al. (2015) was an early prototype of CDS running in one clinic's perioperative environments, and only development team received alerts. Next steps Murphree et al. (2015) mentions were to proceed from prototype to the next level, which requires much development work. Modaresnezhad et al. (2019) built RxSem system for Prediction of bariatric surgery outcomes. It is a proof-of-concept with a limited dataset. In addition to other suggestions for improving their system, Modaresnezhad et al. (2019) suggest that their method should be tested with using different medical datasets. Ferreira et al. (2019) studied surgery scheduling in hospital ORs and created and Adaptive Business Intelligence (ABI) platform. The challenge of the system is that it is a proof-of-concept, and it should be tested with more complex and wider data (Ferreira et al., 2019). Baig et al. (2012) state that prototype of monitoring system they developed is prepared for testing in a real-world setting, while it might require additional features and refining before it is appropriate for frequent clinical use.

Guédon et al. (2016) developed a system for real-time prediction of procedure duration in laparoscopic cholecystectomies. It was evaluated to be promising tool to predict the remaining procedure duration automatically and objectively and to short waiting times for patients. In order to be optimized, the system may need still more relevant factors, such as surgeon's speed or shortage of personnel, to be added (Guédon et al., 2016). The system of da Silveira Grübler et al. (2018) is a model for bed management. In their future work, da Silveira Grübler et al. (2018) are planning to improve some details in techniques they used (more usable values for ANN training and more values for status parameters for multiattribute value theory). Fairley et al. (2019) created a three-part surgical patient sequencing strategy to reduce the PACU overcrowding and resulting OR delays. Further simulation model improvement is planned for the Fairley et al. (2019) system, and it would result in a more accurate assessment of the performance of the scheduling system.

5. Discussion

This section presents both general observations of the SLR and the answers to the research questions. The research question of this SLR was “How is AI currently utilized in patient flow management in the context of perioperative care?” Chapter 5.1 summarizes key findings of this SLR and presents how the results have been analyzed. Results of the SLR shows that there are still very few studies on the subject. According to the results of primary studies, versatile AI techniques were used. Chapter 5.2 describes AI classification in each CDS category, and what features were found from the primary studies. The majority of the applications found from the studies concentrated on relatively narrow functional areas and patient conditions. That and other aspects of challenges and future suggestions are discussed in Chapter 5.3.

5.1 Summary of key findings

Artificial intelligence system functionalities could be critical in perioperative patient flow. A relatively small number of studies (n=33) were found in this review, and we decided to include all studies which fulfilled the inclusion criteria of focusing on patient flow, on AI, and on perioperative care. The nature of this study was to find the state-of-the art in the industry. As a result, we also wanted to include early test results and proof-of-concepts for AI applications that were somehow integrated into the perioperative patient flow. This SLR found clinical tasks of CDS systems under expert systems and workflow support. The challenge of defining the type of the functionalities of the CDS systems was that each system focused on different types of clinical tasks at different perioperative phases and patient conditions. The systems did not have many similarities in tasks and categorization was challenging at first. We were able to utilize the categorization of CDS systems developed by Wright et al. (2011), and this categorization gave structure when we were evaluating and synthesizing primary studies.

The expert systems categorization was based on the Wright et al. (2011) review as the present review was able to find same subcategories in primary studies. Subcategories under expert systems were risk assessment, treatment planning, diagnostic support, prognostic tools and transfusion support. The eight solutions which had workflow support functionalities were not included in the Wright et al. (2011) categorization of CDS systems. Those systems had the subcategories surgical workflow detection, OR scheduling, bed management and automation of clinical processes. It can be assumed that CDS systems were still rapidly evolving on the 2010s and have been undergoing significant changes and advancements during the time until today. When Wright et al. (2011) prepared their research, commercial vendors did not yet offer such broad workflow support functionalities on their systems. This is the why our review was able to find new subcategories of workflow support from primary studies.

CDS functionalities found in the primary studies of the present SLR’s had many interventions and functionalities to help clinicians on the perioperative decision-making. Those features not only reduce the risk of complications during surgery but also help in optimizing the use of resources and improving patient outcomes. They enable healthcare providers to make data-driven decisions and enhance the overall efficiency of the healthcare system. Therefore, the need for these functionalities cannot be overstated in the perioperative patient flow. The next chapter summarizes the AI classifications and features found in the primary studies.

5.2 AI classifications versus features in the primary studies

As mentioned before, many AI categories were found in the primary studies. All 11 risk assessment tools utilized ML on their functionalities. Also, the prognostic tools and transfusion support solutions, altogether four studies, mentioned ML as an AI category used in their solutions. The interventions and features for which systems were designed were preoperative prediction, improving surgeons' point-of-care decision-making by improving patient risk assessment, helping with decision making and event prevention by identifying patients who are at risk, surgical risk prediction, preoperative patient optimization, postoperative complication risk prediction, risk calculator, analysis and visualization of structured EHR data and interventions of helping healthcare professionals in decision-making during prognosis. Those features include a large amount of data fetched from patient EHRs and combed with different datasets. The process of combining data from several sources into a data storage is known as data integration. The reason for the utilizing ML algorithms within these tools can be the need to process structured EHR data and data from many sources. For example, Murphree et al. (2015) described their system to be able to fetch data from several data sources such as electronic medical records, sensor data which records physiological measurements, invoicing data, laboratory data and pharmacy history. According Murphree et al. (2015), data sources are pipelines through which input data gets fed into the system. Also, Isoviita et al. (2019) emphasize that their system is able to fetch and merge data from multiple sources, which enables the creation of predictive models for the analysis of integrated perioperative dissemination data and preoperative clinical data. The findings of Isoviita et al. (2019) show the value of combining data from many sources.

Treatment planning, diagnostic support and workflow support solutions exploited more diverse AI techniques than risk assessment tools, prognostic tools and transfusion support. AI categories that were utilized in the treatment planning systems were ML, CBR, rule-based algorithms and rule-based semantic networks. AI categories used in the diagnostic support category's solutions were fuzzy-logic, NLP (text mining), pattern-matching algorithm and ML. Treatment planning AI solutions support decision-making and helps in treatment planning, builds estimates of the outcomes, decision support during complex surgery or minimally invasive surgery, enhances situational awareness and automates clinical processes, predicting surgery outcomes, predicts postoperative outcomes and provides operational support. Diagnostic support can help with diagnosing possible events in anaesthetized patients, identify and classify allergies related to aesthesia during surgery, help in preoperative planning and detect and surveillance of medical conditions from unstructured texts of EHR. NLP, pattern-matching and rule-based algorithms are justified to be used for example in searching unstructured text-based data from the patient narratives.

AI techniques ML (DL), CV, ANN and rule-based algorithms were found in the eight solutions which were categorized as workflow support. Workflow support had interventions such as surgical workflow detection, OR scheduling; patient flow in OR and PACU, reducing the PACU overcrowding and resulting OR delays, reducing the shifts wasted, enhancing OR efficiency, addressing the fragile surgical waiting lists situation and real-time prediction of procedure duration. Tools for situation awareness in bed management and automation of clinical processes were found as well. In conclusion, the functionalities offered by the workflow support category are related to the identification of stages of the patient flow. Therefore, it can benefit from, for example, AI techniques such as CV and rule-based algorithms.

5.3 Challenges and future suggestions in the primary studies

AI systems face several challenges in the perioperative patient flow. One of the major challenges which is discovered in this SLR is the lack of holistic patient care. The majority of the applications found in the studies concentrated on relatively narrow functional areas and patient conditions. Many of the functionalities concentrated on specific tasks or procedures, and the bigger picture of patient's treatment could not be addressed. The primary studies were quite different compared to each other, and they did not give suggestions on building more holistic systems. Another challenge was the variability in patient profiles and clinical conditions. AI systems need to be able to adapt to different patient populations and respond to unexpected events or complications during surgery. This requires robust algorithms and continuous monitoring of patient data. At the moment, hospital IS are fragmented into many separate systems, and there can be challenges in fetching varying data from many sources (Aikemu et al., 2021; Yun et al., 2021; Somashekhar et al., 2018; Gonçalves et al., 2021; Bishara et al., 2021; Dantes et al., 2018). Hence, a challenge emerges also in integrating AI systems into existing clinical workflows and systems. The interoperability of different systems and the ability to transfer patient data between them is crucial for the success of AI systems in the perioperative setting.

One concern is the ethical questionability of flawed systems. Isoviita et al. (2019) developed a system which allows analysis and visualization of structured EHR data and draws predictions based on it. However, the research report does not describe whether the system would offer alternatives to therapy, and because of this, the system is ethically questionable. All in all, some of the studies draw their conclusions only from test data, their solutions are proof-of-concepts or do not run in a real production environment and therefore, their results cannot be generalized. One ethical concern are biased algorithms. There may be gaps and missing values or variables in the patient data, and therefore some measurements can be biased (Berge et al., 2017; Babic et al., 2014; Gonçalves et al., 2021; Bishara et al., 2021; Bertsimas et al., 2019; Navarese et al., 2021).

Previous studies have found that the growth in the utilizing of AI today requires cooperation of many stakeholders in hospitals, institutions, and commercial vendors. The concern of losing control in the Human-AI interaction and developing so called "black-boxes" have been raised before (Holzinger et al., 2019). Previous research emphasizes the importance of transparency (Holzinger et al., 2019) and explainability (Bodenstedt et al., 2020) in the systems. Domain expertise and involving professionals from computer scientists, clinical researchers, clinicians, and other stakeholders and users is crucial (Holzinger et al., 2019; Bodenstedt et al., 2020; Bellini et al., 2022; Simon et al., 2019; Hashimotoet al., 2018; Lopez-Jimenez et al., 2020). The need for involving clinicians in the design and implementation of AI systems and algorithms was recognized also in this SLR (Hur et al., 2020; Brennan et al., 2019).

The healthcare sector is strictly regulated and that adds challenges to the requirements for AI systems. Actions in regulation and standardization are needed (Davenport & Kalakota, 2019). Further research is needed to validate and optimize the application of AI in perioperative patient flow. None of the primary studies in this SLR brought up regulation requirements in their systems.

6. Conclusions

The purpose of this thesis was to map the existing landscape of artificial intelligence (AI) applications used in secondary healthcare, with a focus on perioperative care. The goal was to find out what systems have been developed, and how capable they are at controlling perioperative patient flow. The review was guided by the following research question: How is AI currently utilized in patient flow management in the context of perioperative care?

Solutions primarily consisted of tasks of CDS systems and belonged in the category of expert systems and workflow tools. This suggests that AI technology is being employed to provide decision-making support and enhance the overall workflow in perioperative patient care. The use of CDS tools indicates that AI systems are designed to assist healthcare professionals in making informed decisions during the perioperative process. These tools could potentially offer recommendations, guidelines or predictions based on patient data and medical knowledge and that would help to improve efficiency, accuracy, and patient outcomes.

The results show that the use of artificial intelligence is still quite a new and developing domain in the healthcare sector. Trends that can be found in the background and in the functionalities in the primary studies are data pooling and analytics, including data integration, AI and automatization of the acquirement and analysis of relevant data from multiple sources. AI based decision support can support clinicians in their daily work and streamline patient flow. That requires modular systems, automatic structured EHR, data sharing between separate EHR's, and acquiring and handling of both structured and unstructured data.

Decision support tools make it possible to analyze more data; the more accurate information can be acquired, the better decisions can be made. AI can assist in managing big data, merging data from many sources, and pattern detection, all of which were previously impossible without the help of AI. Even if a system utilizes ML or any other AI categories, decisions are still made by a physician and the system is human controlled. AI can make suggestions, but a proposition is always evaluated by a medical professional based on the expertise and ethical understanding of what is best for the patient. Nevertheless, AI is superior in collecting, gathering, and analysing data.

When thinking about explainability in healthcare AI systems, there are numerous questions. How decision-making algorithms can be transparent? How can human practitioners of algorithms understand them in a meaningful way? Can patients believe in the recommendations made by AI? There is clear evidence that AI may be very helpful when determining a diagnosis and prognosis. But when a designer makes explainability characteristics visible, both the medical and patient viewpoints must be considered.

Finally, ethical considerations such as privacy, transparency, and accountability need to be addressed when developing and implementing AI systems in healthcare. The use of patient data for learning algorithms and decision-making processes must be carefully regulated, and patients must be informed about the use of their data and have the right to opt out. Data ownership, data usage and data privacy are some of the most important questions and need regulation.

This review demonstrates how AI can affect multiple aspects of patient flow in perioperative care at various levels of care; however, further study is necessary to find ways to utilize AI more comprehensively.

6.1 Study limitations

This SLR only included research literature, which is usually out of date and does not fully describe the current situation. Due to the lack of comprehensive research on commercial off-the-shelf products, there is no up-to-date data on which applications are actually being used or developed now.

One limitation is that searches were performed only in four databases: Scopus, Web of Science, Ovid MEDLINE, and PubMed. A more thorough search across other databases might have produced more recent studies. This study also has a limitation in that an independent quality assessment was not carried out. Because of the limited number of primary studies, we decided to include all studies that met the inclusion criteria by having to focus on patient flow, AI, and perioperative care. We also intended to provide early test results and proof-of-concepts for AI applications that were integrated into the perioperative patient flow.

6.2 Future research

AI solutions in healthcare is a large topic, and the information provided by perioperative care in this case was both interesting and useful. This review was able to address many challenges and future suggestions based on the primary studies. The majority of the studies concentrated only on specific tasks or procedures. None of the systems fit in the definition of a holistic system. AI systems need to be able to adapt to different patient populations and respond to unexpected events or complications during surgery. The interoperability of different systems and the ability to transfer patient data between them is crucial for the success of AI systems in the perioperative setting.

One thing to be concerned about is how ethically questionable flawed systems are. Many of the systems were still on the proof-of-concept level or based on the test data, and their results thus cannot be generalized in real life. Due to the gaps and missing values in the patient data, some measurements can be biased. Building transparent, inclusive, and understandable solutions would be possible with the help of many stakeholders and domain specialists in hospitals, institutions, and commercial vendors. The highly regulated nature of the healthcare industry makes the requirements for AI systems more complex. There is a need for regulation and standardization actions. The issues and factors to be considered while creating AI systems for perioperative patient flow are outlined in Figure 7.

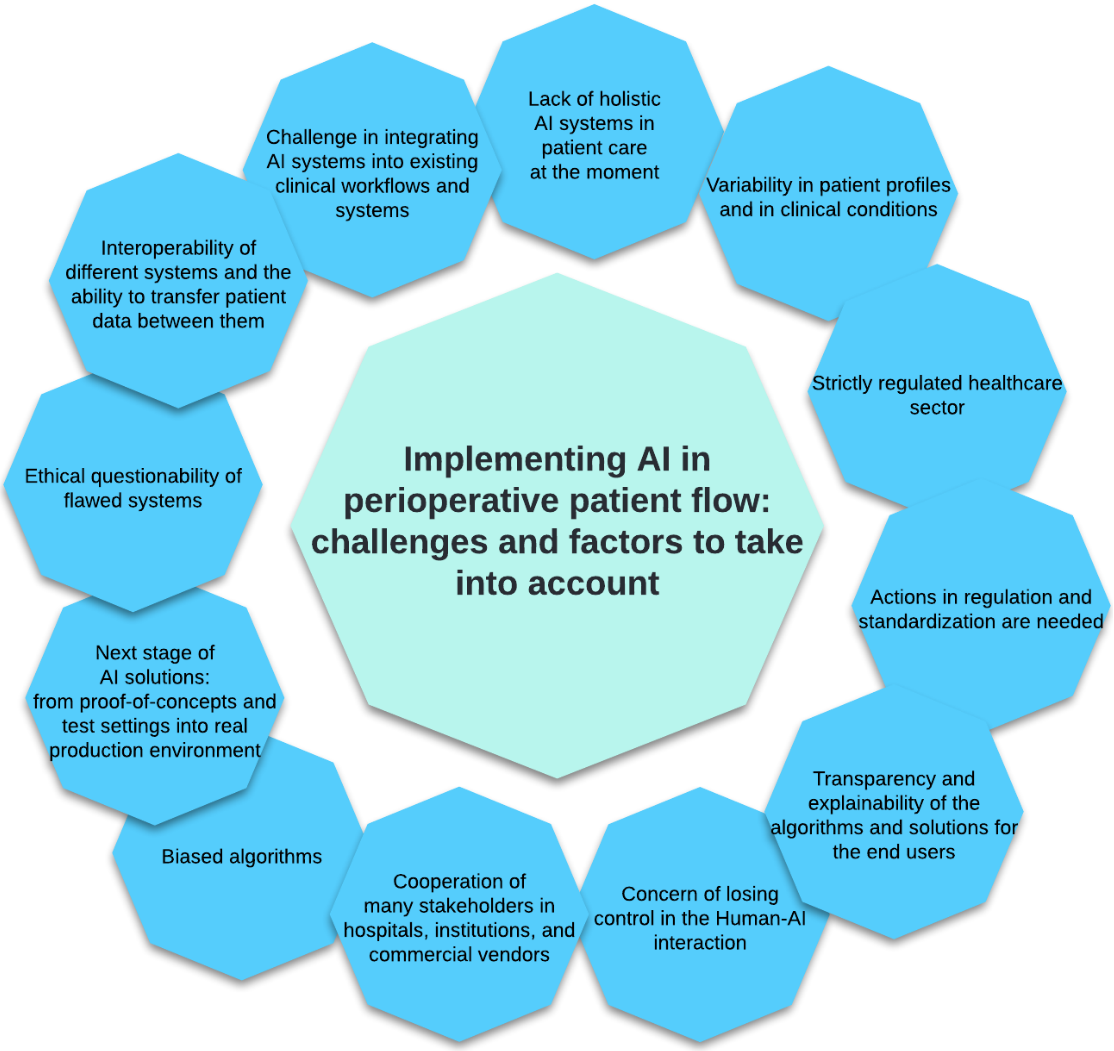

Figure 7. Challenges and factors to take into account while implementing AI systems

Further research is needed to develop and optimize AI tools for perioperative care. However, as healthcare AI solutions as a topic is already broad, and affects holistic patient IS much more widely, I recommend it to be treated more widely as its own further research topic. Utilizing AI becomes more important in the future and healthcare providers, institutions and commercial EHR vendors should involve it in their future plans covering all solutions. It is time to start discussing and planning the framework for building AI systems in healthcare and perioperative care. For that, cooperation between different stakeholders is strongly advised. While the scope of this SLR did not include deeply analyzing the used AI techniques or algorithms, their properties and effectiveness in the possible solutions should be evaluated in future studies.

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Appendix A: Studies whose search terms were used in the search string

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Appendix B. Search strings in each database

Scopus (n=2084)
TITLE-ABS-KEY ("patient flow" OR "flow of patients" OR "patients' flow" OR "patient transfer" OR "patient process" OR "flow of care" OR "patient admission" OR "organizational efficiency" OR "access time" OR "bed occupancy" OR "capacity allocation" OR "capacity management" OR "capacity planning" OR "care management" OR "patient pathway" OR "patient route" OR "patient throughput" OR "process flow" OR "wait time" OR "waiting list" OR "waiting time" OR "length of stay" OR "care access" OR "demand management" OR "clinical pathway" OR "treatment pathway" OR "patient journey" OR "patient care process" OR "patient flow logistic*" OR "key performance indicator*" OR "lean healthcare" OR "patient turnover" OR "length of stay" OR caseload OR workload OR "decision support" AND preoperat* OR postoperat* OR intraoperat* OR perioperat* OR pre-operat* OR per-operat* OR peri-operat* OR post-operat* OR intra-operat* OR "operating theatre" OR "operating room*" OR surgery OR surger* OR surgic* OR "emergency service" OR "post anasthesia care unit" OR "operative triage" OR anesthe* OR anaesthe* OR trauma OR "enhanced recovery" OR "rapid recovery" AND "artificial intelligence" OR "big data" OR "machine learning" OR "deep learning" OR "pattern Recognition" OR "automated intelligence" OR "data mining" OR "neural network*" OR "computer-assisted diagnosis" OR "computer assisted diagnosis" OR "computer-aided diagnosis" OR "computer aided diagnosis")

Web of science (n=711)
TS=("patient flow" OR "flow of patients" OR "patients' flow" OR "patient transfer" OR "patient process" OR "flow of care" OR "patient admission" OR "organizational efficiency" OR "access time" OR "bed occupancy" OR "capacity allocation" OR "capacity management" OR "capacity planning" OR "care management" OR "patient pathway" OR "patient route" OR "patient throughput" OR "process flow" OR "wait time" OR "waiting list" OR "waiting time" OR "length of stay" OR "care access" OR "demand management" OR "clinical pathway" OR "treatment pathway" OR "patient journey" OR "patient care process" OR "patient flow logistic*" OR "key performance indicator*" OR "lean healthcare" OR "patient turnover" OR "length of stay" OR caseload OR workload OR "decision support") AND TS=(preoperat* OR postoperat* OR intraoperat* OR perioperat* OR pre-operat* OR per-operat* OR peri-operat* OR post-operat* OR intra-operat* OR "operating theatre" OR "operating room*" OR surgery OR surger* OR surgic* OR "emergency service" OR "post anasthesia care unit" OR "operative triage" OR anesthe* OR anaesthe* OR trauma OR "enhanced recovery" OR "rapid recovery") AND TS=("artificial intelligence" OR "big data" OR "machine learning" OR "deep learning" OR "pattern Recognition" OR "automated intelligence" OR "data mining" OR "neural network*" OR "computer-assisted diagnosis" OR "computer assisted diagnosis" OR "computer-aided diagnosis" OR "computer aided diagnosis")

Ovid Medline (n=1321)
(("patient flow" OR "flow of patients" OR "patients' flow" OR "patient transfer" OR "patient process" OR "flow of care" OR "patient admission" OR "organizational efficiency" OR "access time" OR "bed occupancy" OR "capacity allocation" OR "capacity management" OR "capacity planning" OR "care management" OR "patient pathway" OR "patient route" OR "patient throughput" OR "process flow" OR "wait time" OR "waiting list" OR "waiting time" OR "length of stay" OR "care access" OR "demand management" OR "clinical pathway" OR "treatment pathway" OR "patient journey" OR "patient care process" OR "patient flow logistic*" OR "key performance indicator*" OR "lean healthcare" OR "patient turnover" OR "length of stay" OR caseload OR workload OR "decision support") and (preoperat* OR postoperat* OR intraoperat* OR perioperat* OR pre-operat* OR per-operat* OR peri-operat* OR post-operat* OR intra-operat* OR "operating theatre" OR "operating room*" OR surgery OR surger* OR surgic* OR "emergency service" OR "post anasthesia care unit" OR "operative triage" OR anesthe* OR anaesthe* OR trauma OR "enhanced recovery" OR "rapid recovery") and ("artificial intelligence" OR "big data" OR "machine learning" OR "deep learning" OR "pattern Recognition"

OR "automated intelligence" OR "data mining" OR "neural network*" OR "computer-assisted diagnosis" OR "computer assisted diagnosis" OR "computer-aided diagnosis" OR "computer aided diagnosis")).af.

PubMed (n=469)
(("patient flow"[Title/Abstract] OR "flow of patients"[Title/Abstract] OR "patients' flow"[Title/Abstract] OR "patient transfer"[Title/Abstract] OR "patient process"[Title/Abstract] OR "flow of care"[Title/Abstract] OR "patient admission"[Title/Abstract] OR "organizational efficiency"[Title/Abstract] OR "access time"[Title/Abstract] OR "bed occupancy"[Title/Abstract] OR "capacity allocation"[Title/Abstract] OR "capacity management"[Title/Abstract] OR "capacity planning"[Title/Abstract] OR "care management"[Title/Abstract] OR "patient pathway"[Title/Abstract] OR "patient route"[Title/Abstract] OR "patient throughput"[Title/Abstract] OR "process flow"[Title/Abstract] OR "wait time"[Title/Abstract] OR "waiting list"[Title/Abstract] OR "waiting time"[Title/Abstract] OR "length of stay"[Title/Abstract] OR "care access"[Title/Abstract] OR "demand management"[Title/Abstract] OR "clinical pathway"[Title/Abstract] OR "treatment pathway"[Title/Abstract] OR "patient journey"[Title/Abstract] OR "patient care process"[Title/Abstract] OR "patient flow logistic*"[Title/Abstract] OR "key performance indicator*"[Title/Abstract] OR "lean healthcare"[Title/Abstract] OR "patient turnover"[Title/Abstract] OR caseload[Title/Abstract] OR workload[Title/Abstract] OR "decision support"[Title/Abstract]) AND (preoperat*[Title/Abstract] OR postoperat*[Title/Abstract] OR intraoperat*[Title/Abstract] OR perioperat*[Title/Abstract] OR pre-operat*[Title/Abstract] OR per-operat*[Title/Abstract] OR peri-operat*[Title/Abstract] OR post-operat*[Title/Abstract] OR intra-operat*[Title/Abstract] OR "operating theatre"[Title/Abstract] OR "operating room*"[Title/Abstract] OR surgery[Title/Abstract] OR surger*[Title/Abstract] OR surgic*[Title/Abstract] OR "emergency service"[Title/Abstract] OR "post anasthesia care unit"[Title/Abstract] OR "operative triage"[Title/Abstract] OR anesthe*[Title/Abstract] OR anaesthe*[Title/Abstract] OR trauma[Title/Abstract] OR "enhanced recovery"[Title/Abstract] OR "rapid recovery"[Title/Abstract]) AND ("artificial intelligence"[Title/Abstract] OR "big data"[Title/Abstract] OR "machine learning"[Title/Abstract] OR "deep learning"[Title/Abstract] OR "pattern Recognition"[Title/Abstract] OR "automated intelligence"[Title/Abstract] OR "data mining"[Title/Abstract] OR "neural network*"[Title/Abstract] OR "computer-assisted diagnosis"[Title/Abstract] OR "computer assisted diagnosis"[Title/Abstract] OR "computer-aided diagnosis"[Title/Abstract] OR "computer aided diagnosis"[Title/Abstract]))

Appendix C. Extraction table

The data extracted from each paper was:

- General information about the study
    a) Article author(s)
    b) Publication year
    c) Article title
    d) Journal/Conference
    e) DOI
    f) Keywords
    g) Abstract

- Specific information about the study
    h) The main topic of article
    i) Research method
    j) Research questions
    k) How much and what kind of data has been collected the research
    l) Hospital and/or country
    m) Disease/condition that the article deals with
    n) Definition of AI
    o) What specific AI technology /technologies have been utilized/studied?
    p) What is the ”perioperative care” study context/aspect in which the study has been conducted?
    q) What is the "patient flow" aspect that the study addresses / is related to?
    r) How is AI in patient flow management “approached” in the article?
    s) Benefits of AI use identified?
    t) Challenges of AI use identified?
    u) Future research / suggestions
    v) User interface / application / platform, how it is described in the article?
    w) Summary of the research (in own words)

Appendix D. Data collected from primary studies

Author	Perioperative phase, where AI is used	Perioperative care context for the solution	Research country	Disease / condition	Cancer	AI technology	Patient flow aspect	AI in patient flow approach	Benefits of AI use	Challenges of AI use	Description of user interface, application or platform	Future research suggestions
Aikemu et al., 2021	x	x	x	x	x	x	x	x	x	x	x	x
Babic et al., 2014	x		x	x		x	x			x	x	x
Baig et al., 2012	x	x	x	x		x	x		x		x	
Bar et al., 2020	x		x	x		x	x				x	x
Berge et al., 2017	x	x	x	x		x	x		x	x	x	
Bertsimas et al., 2018	x		x			x	x		x		x	x
Bishara et al., 2021	x		x			x	x			x	x	x
Brennan et al., 2019	x		x			x	x		x		x	
Ciofi Degli Atti et al., 2020	x		x	x		x	x	x			x	x
Cole et al., 2021	x		x	x		x	x	x			x	x
Corey et al., 2018	x	x	x			x	x		x		x	x
Dantes et al., 2018	x	x	x	x		x	x		x		x	x
Datta et al., 2020	x	x	x			x	x				x	x
El-Fakdi and Gamero, 2014	x	x	x	x		x	x				x	x
Fairley et al., 2019	x		x			x	x				x	
Ferreira et al., 2019	x		x			x	x			x	x	
Goncalves et al., 2021	x		x	x	x	x	x		x	x	x	
Grubler et al., 2018	x	x	x			x	x				x	
Guedon et al., 2016	x		x	x		x	x				x	
Hur et al., 2020	x		x	x		x	x				x	x
Isoviita et al., 2019	x		x	x	x	x	x				x	
Jordan and Rose, 2010	x		x			x	x		x		x	
Lv et al., 2021	x	x	x	x	x	x	x				x	
Modaresnezhad et al., 2019	x	x	x	x		x	x				x	
Murphree et al., 2015	x	x	x	x		x	x				x	
Navarese et al., 2021	x		x	x		x	x				x	
Oliveira et al., 2013	x	x	x	x	x	x	x				x	
Perkins et al., 2020	x		x	x		x	x				x	
Pierce et al., 2021	x		x	x		x	x		x		x	x
Shabaniyan et al., 2019	x	x	x	x		x	x				x	
Somashekhar et al., 2018	x	x	x	x	x	x	x				x	x
Sperandio et al., 2014	x		x			x	x	x	x		x	
Yun et al., 2021	x		x	x	x	x	x	x			x	x

Appendix E. List of Primary Studies

Author(s)	Title	Study ID
Aikemu, B., Xue, P., Hong, H., Jia, H., Wang, C., Li, S., ... & Sun, J. (2021)	Artificial Intelligence in Decision-Making for Colorectal Cancer Treatment Strategy: An Observational Study of Implementing Watson for Oncology in a 250-Case Cohort	[P1]
Babic, A., Peterzen, B., Lönn, U., & Ahn, H. C. (2014)	Case Based Reasoning in a web based decision support system for thoracic surgery	[P2]
Baig, M. M., Gholamhosseini, H., & Harrison, M. J. (2012)	Fuzzy logic based smart anaesthesia monitoring system in the operation theatre	[P3]
Bar, O., Neimark, D., Zohar, M., Hager, G. D., Girshick, R., Fried, G. M., ... & Asselmann, D. (2020)	Impact of data on generalization of AI for surgical intelligence applications	[P4]
Berge, G.T., Granmo, O., & Tveit, T.O. (2017)	Combining unsupervised, supervised, and rule-based algorithms for text mining of electronic health records: A clinical decision support system for identifying and classifying allergies of concern for anesthesia during surgery	[P5]
Bertsimas, D., Dunn, J., Velmahos, G. C., & Kaafarani, H. M. (2018)	Surgical Risk Is Not Linear: Derivation and Validation of a Novel, User-friendly, and Machine-learning-based Predictive OpTimal Trees in Emergency Surgery Risk (POTTER) Calculator	[P6]
Bishara, A., Wong, A., Wang, L., Chopra, M., Fan, W., Lin, A., ... & Butte, A. (2021)	Opal: an implementation science tool for machine learning clinical decision support in anesthesia	[P7]
Brennan, M., Puri, S., Ozrazgat-Baslanti, T., Feng, Z., Ruppert, M., Hashemighouchani, H., ... & Bihorac, A. (2019)	Comparing clinical judgment with the MySurgeryRisk algorithm for preoperative risk assessment: A pilot usability study	[P8]
Ciofi Degli Atti, M. L., Pecoraro, F., Piga, S., Luzi, D., & Raponi, M. (2020)	Developing a Surgical Site Infection Surveillance System Based on Hospital Unstructured Clinical Notes and Text Mining.	[P9]
Cole, J., Hughey, S., Metzger, A., Geiger, P., Fluke, L., & Booth, G. J. (2021)	Machine Learning to Predict Fascial Dehiscence after Exploratory Laparotomy Surgery	[P10]
Corey, K. M., Kashyap, S., Lorenzi, E., Lagoo-Deenadayalan, S. A., Heller, K., Whalen, K., ... & Sendak, M. (2018)	Development and validation of machine learning models to identify high-risk surgical patients using automatically curated electronic health record data (Pythia): A retrospective, single-site study.	[P11]
Dantes, R. B., Zheng, S., Lu, J. J., Beckman, M. G., Krishnaswamy, A., Richardson, L. C., ... & Wang, F. (2018)	Improved Identification of Venous Thromboembolism from Electronic Medical Records Using a Novel Information Extraction Software Platform	[P12]
Datta, S., Loftus, T. J., Ruppert, M. M., Giordano, C., Upchurch Jr, G. R., Rashidi, P., ... & Bihorac, A. (2020)	Added Value of Intraoperative Data for Predicting Postoperative Complications: The MySurgeryRisk PostOp Extension	[P13]

El-Fakdi, A., & Gamero, F. (2014)	EXiTCDSS: A framework for a workflow-based CBR for interventional clinical decision support systems and its application to TAVI	[P14]
Fairley, M., Scheinker, D., & Brandeau, M. L. (2019)	Improving the efficiency of the operating room environment with an optimization and machine learning model.	[P15]
Ferreira, J., Portela, F., Machado, J., & Santos, M. F. (2019)	Adaptive business intelligence in healthcare - A platform for optimising surgeries	[P16]
Gonçalves, D., Henriques, R., Santos, L. L., & Costa, R. S. (2021)	On the predictability of postoperative complications for cancer patients: a Portuguese cohort study.	[P17]
da Silveira Grübler, M., da Costa, C. A., da Rosa Righi, R., Rigo, S. J., & Chiwiacowsky, L. D. (2018)	A Hospital Bed Allocation Hybrid Model Based on Situation Awareness	[P18]
Guédon, A. C., Paalvast, M., Meeuwsen, F. C., Tax, D. M., van Dijke, A. P., Wauben, L. S. G. L., ... & van den Dobbelsteen, J. J. (2016)	It is Time to Prepare the Next patient' Real-Time Prediction of Procedure Duration in Laparoscopic Cholecystectomies.	[P19]
Hur, C., Wi, J., & Kim, Y. (2020)	Facilitating the development of deep learning models with visual analytics for electronic health records	[P20]
Isoviita, V. M., Salminen, L., Azar, J., Lehtonen, R., Roering, P., Carpén, O., ... & Hautaniemi, S. (2019)	Open source infrastructure for health care data integration and machine learning analyses	[P21]
Jordan, D., & Rose, S. E. (2010)	Multimedia abstract generation of intensive care data: the automation of clinical processes through AI methodologies	[P22]
Lv, S., Li, S., Yu, Z., Wang, K., Qiao, X., Gong, D., & Wu, C. (2021)	Application of the Preoperative Assistant System Based on Machine Learning in Hepatocellular Carcinoma Resection	[P23]
Modaresnezhad, M., Vahdati, A., Nemati, H., Ardestani, A., & Sadri, F. (2019)	A rule-based semantic approach for data integration, standardization and dimensionality reduction utilizing the UMLS: Application to predicting bariatric surgery outcomes	[P24]
Murphree, D. H., Clifford, L., Lin, Y., Madde, N., Ngufor, C., Upadhyaya, S., ... & Kor, D. J. (2015)	A clinical decision support system for preventing adverse reactions to blood transfusion	[P25]
Navarese, E. P., Zhang, Z., Kubica, J., Andreotti, F., Farinaccio, A., Bartorelli, A. L., ... & a Joint Effort of the Italian and Polish Cardiac Interventional Societies. (2021)	Development and Validation of a Practical Model to Identify Patients at Risk of Bleeding After TAVR	[P26]
Oliveira, T., Barbosa, E., Martins, S., Goulart, A., Neves, J., & Novais, P. (2013)	A prognosis system for colorectal cancer	[P27]
Perkins, Z. B., Yet, B., Sharrock, A., Rickard, R., Marsh, W., Rasmussen, T. E., & Tai, N. R. (2020)	Predicting the Outcome of Limb Revascularization in Patients With Lower-extremity Arterial Trauma: Development and External Validation of a Supervised Machine-learning Algorithm to Support Surgical Decisions	[P28]

Pierce, K. E., Kapadia, B. H., Naessig, S., Ahmad, W., Vira, S., Paulino, C., ... & Passias, P. G. (2021)	Validation of the ACS-NSQIP Risk Calculator: A Machine-Learning Risk Tool for Predicting Complications and Mortality Following Adult Spinal Deformity Corrective Surgery.	[P29]
Shabaniyan, T., Parsaei, H., Aminsharifi, A., Movahedi, M. M., Jahromi, A. T., Pouyesh, S., & Parvin, H. (2019)	An artificial intelligence-based clinical decision support system for large kidney stone treatment.	[P30]
Somashekhar, S. P., Sepúlveda, M. J., Puglielli, S., Norden, A. D., Shortliffe, E. H., Kumar, C. R., ... & Ramya, Y. (2018)	Watson for Oncology and breast cancer treatment recommendations: agreement with an expert multidisciplinary tumor board.	[P31]
Sperandio, F., Gomes, C., Borges, J., Brito, A. C., & Almada-Lobo, B. (2013)	An intelligent decision support system for the operating theater: A case study	[P32]
Yun, H. J., Kim, H. J., Kim, S. Y., Lee, Y. S., Lim, C. Y., Chang, H. S., & Park, C. S. (2021)	Adequacy and Effectiveness of Watson For Oncology in the Treatment of Thyroid Carcinoma.	[P33]