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Artificial Intelligence Changing the Surgical Field, Specifically Transplantation: A Systematic Review

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Abstract:

Artificial Intelligence (AI) has become one of the trendiest topics around the world. AI has been transforming traditional methods into innovative new approaches in medicine. The main question we want to address in this paper is to see how AI helps surgeons and what challenges AI can present in transplantation. In this study, we reviewed published articles from PubMed, Google Scholar, PMC, MEDLINE, and Cochrane Library. We assessed each paper with our inclusion/exclusion criteria, which included papers published between 2019 and 2024, available as free-text articles, and written in English. We included published papers that talked about adult kidney, liver, and heart transplantation in humans. Any papers that contained only other types of transplantation, like lungs or orthopedic, were not included. We excluded papers that included pediatric or animal studies. We used 12 articles to finalize this systematic review. We used the MeSH terminology ("Artificial Intelligence"[MeSH]) AND ("Transplantation/adverse effects"[MeSH] OR "Transplantation/methods"[MeSH]), and the keywords were "Artificial Intelligence, Machine learning, Deep learning, Transplant Surgery, Artificial Neural Networks, and Transplantation". The systematic reviews will discuss the potential benefits of decision-making and pre-operative or post-operative management, taking into consideration that further studies are needed to finalize conclusions on the effectiveness of AI in the surgical field, as this is a relatively new implementation.

Introduction:

Artificial Intelligence (AI) is defined as the theory and development of computer systems capable of performing tasks that typically require human intelligence. Examples of these computer systems include visual perception, speech recognition, decision-making, and translation between languages. Alan Turing, in 1947, was one of the first to propose the idea that computer systems can work imitating human intelligence, his work bringing advancement in AI [1]. In recent years, AI has rapidly become a trendy topic due to years of research finally reaching a point where we can utilize AI for practical applications. AI has increased fear and admiration due to these computer systems being able to exceed and even outthink humans [2]. AI is ready to transform many industries by creating different ways humans and machines can work together [3].

AI has become a new tool that is gaining attraction in healthcare, indicating a shift to digital technology in the medical field [4]. Healthcare practices, research, and applications are anticipated to have improved precision with the help of AI [5]. In surgery, AI has become more important due to helping patients and surgeons with decision-making since AI foreshadows surgical outcomes [6]. Therefore, surgeons should have a better understanding of this technology to explore ways in which AI can be utilized in the surgical field [2]. Machine Learning (ML), a subclass of AI, generates predictions and decisions by examining vast amounts of information. ML has been used for many healthcare functions, including the identification of possible neoplasms using MRI, X-rays, or CT scans, as well as data collection to detect risks. Knowing when a patient must be admitted, predicting mortality, or if a patient will need to be re-admitted following surgery [4]. ML also has a subclassification called Deep Learning (DL), which imitates the human brain's functions using artificial neural networks (ANNs). With ongoing training of these models, we can enhance predictions and accuracy [1].

Transplantation is the process of taking an organ or living tissue and implanting it in another part of the body or in someone else. Transplantation of organs is a subspecialty of the surgical field and one that comes with many challenges. These types of surgeries tend to be very expensive and have many ethical dilemmas [7]. ML identifies non-linear connections and influencing factors that were considered of limited value. Using these new variables, ML helps surgeons anticipate post-transplantation rejection likelihood and determine waitlist mortality [8]. Another influencing factor for using AI in transplants is that it may enhance the matching process between donors and recipients. It can also help surgeons make specific plans for the individual in care, evaluating different risks for patient noncompliance [9].

AI has not been widely utilized in the field of transplantation; to date, no AI tools for transplantation have received FDA approval [9]. As AI continues to grow and be clinically implemented in medicine and surgery, it will be essential to adhere to guidelines and

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continually revise them to make proper changes [5]. Within this systematic review, we aim to discuss different ways in which AI is helping the surgical field, with a focus on organ transplantation. AI has been continuously growing; in Figure 1, we will see its evolution throughout the years [10].

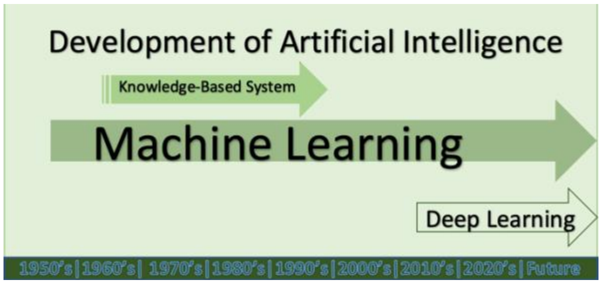

Figure 1: Timeline of the Development of AI.
Image created by the primary author

Methods:

We followed the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) guidelines for this systematic review [11]. We searched PubMed, Google Scholar, PMC, MEDLINE, and Cochrane Library. The Boolean operators used in this systematic review were: AND or OR. This review did not include risk of bias (RoB) assessment for the included studies. As such, this review should be read with discretion. For future reviews, a formal RoB assessment should be included to improve reliability. Table 1 shows the data from each database:

Table 1: Demonstrates how many papers were found on each database

Databases	Terminology	Number of papers
Google Scholar	allintitle: and transplantation "artificial intelligence"	45
MeSH terminology /MEDLINE	("Artificial Intelligence"[Mesh]) AND ("Transplantation/adverse effects"[Mesh] OR "Transplantation/methods"[Mesh])	102
PubMed/PMC	artificial intelligence [Title] AND transplantation [Title]	16
Cochrane Library	artificial intelligence and transplantation	4

- Inclusion and Exclusion Criteria

For this systematic review, we included articles published in the last five years (2019-2024) written in English and available as free full text. We used articles that only included adult kidney, liver, or heart transplantations and only used human-published papers. We included primary studies and incorporated other systematic reviews. For the exclusion criteria, we excluded papers published in any language other than English, not full free text, conducted in pediatrics, published only as abstracts, or had access restrictions. We excluded any papers on other transplant surgeries besides the kidney, liver, or heart. We excluded animal studies and did not search grey literature for this systematic review.

- Selection Process

We initially identified a total of 170 publications while searching different databases, 56 of which were relevant and were imported into EndNote for duplicate removal. Endnote found 11 duplicates, which we removed, and 45 remaining articles were screened based on their titles and abstracts. Twenty of these articles were excluded based on titles and abstracts, leaving a total of 25 articles for full-text review.

Of these 25 articles, only 14 met the inclusion and exclusion criteria. However, two failed to meet the quality appraisal threshold of 70% and we did not include them. Ultimately, we included the remaining 12 studies in this systematic review. Figure 2 presents the PRISMA flow diagram detailing the selection process.

- Quality Appraisal of the Shortlisted Articles:

All selected papers that met the inclusion/exclusion criteria underwent quality appraisal based on the type of study. Narrative reviews were assessed using the SANRA scale [12]. All papers that were systematic reviews were assessed using the AMSTAR 2 guidelines [13]. Studies that did not meet 70% of the quality appraisal criteria were excluded from this review. The final 12 papers were carefully reviewed, and all met the quality appraisal results that we were looking for. Tables 2 and 3 present SANRA quality appraisal results, while Table 4 summarizes the AMSTAR 2 quality appraisal results.

Table 2: Quality Appraisal results using the SANRA tool for studies with no defined method section.
SANRA: Scale for the Assessment of Narrative Review Articles

SANRA	Peloso, et al. [3]	Clement et al. [9]	Schwantes, et al. [14]	Rawashdeh, et al. [15]	Balch, et al. [16]
Importance is explicitly justified	2	2	2	2	2
Questions, formulation and aims stated	2	2	2	2	2
Description of literature search	0	0	1	0	0
Key statements are supported	2	2	2	2	2

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by references					
Appropriate evidence is present	2	2	2	2	2
Appropriate presentation of data	2	2	2	2	2

Table 3: Continuation of SANRA quality appraisal
SANRA: Scale for the Assessment of Narrative Review Articles

SANRA	Badrouchi, et al. [17]	Ramalhete et al. [18]	Seyahi, et al. [19]	Bhat, et al. [20]	Veerankutty, et al. [21]
Importance is explicitly justified	2	2	2	2	2
Questions, formulation and aims stated	2	2	2	2	2
Description of literature search	0	0	0	0	0
Key statements are supported by references	2	2	2	2	2
Appropriate evidence is present	2	2	2	2	2
Appropriate presentation of data	2	2	2	2	2

Table 4: Quality Appraisal using AMSTAR guidelines
AMSTAR: Assessing the Methodological Quality of Systematic Review

AMSTAR CHECKLIST	Naruka, et al. [8]	Palmieri, et al. [22]
Did the research question and inclusion criteria include PICO components?	Yes	Yes
Did the review have a registered protocol before starting?	Yes	Yes
Was a comprehensive literature search performed?	Yes	Yes
Were study selection and data extraction done in duplicate?	Yes	Yes
Were exclusions of individual studies explained?	Yes	Yes
Was risk of bias of included studies assessed?	Yes	Yes
Was the risk of bias considered when interpreting results?	Yes	Yes
Were the methods used for statistical combination appropriate?	Yes	Partial Yes
Was heterogeneity investigated and discussed?	No	No
Was publication bias assessed?	No	No
Were the characteristics of included studies described in detail?	Yes	Yes
Were conflicts of interest reported for included studies?	Yes	Yes
Was the funding source of the review reported?	Yes	Yes
Were the results of individual studies adequately considered in discussion?	Yes	Yes
Was an adequate technique used for risk of bias assessment?	Yes	Yes
Did the review interpret results appropriately considering the risk of bias?	Yes	Yes
Results: High result: Zero or non-critical weakness Moderate: More than one weakness, no critical flaws Low: One critical flaw with or without non-critical weakness Critically Low: More than one critical flaw with/without noncritical weakness	High	High

Results:

We identified 170 articles using our keywords and MeSH terms. A total of 56 relevant articles were imported into EndNote to remove all duplicates. 11 duplicate papers were found and excluded, leaving a total of 45 articles that were screened based on titles and abstracts. After a careful review, 20 papers were excluded based on full-text review, leaving 25 papers. Of the 25 papers left, only 14 met our inclusion/exclusion criteria, and 12 met the quality appraisal assessment. Figure 2 presents the PRISMA flow diagram illustrating the study selection process. A Brief discussion of each paper and what each paper aims for can be seen in Table 5:

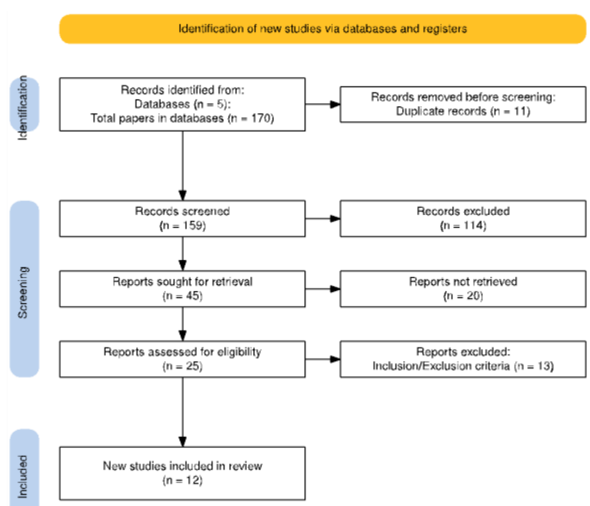

Figure 2: presents the PRISMA flow diagram illustrating the study selection process, including

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the number of studies identified, screened, excluded, and included.
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

Table 5: Brief description of the 12 articles chosen for this systematic review

Author	Year	Study Type	Aim
Peloso, et al. [3]	**2022**	**Traditional Review**	This study identifies areas where Ai can be used in transplant surgery. This study does not target a specific type of transplant surgery but rather discusses approaches where AI may be more useful. Highlighting areas like organ allocation, donor-recipient matches, immunosuppression, transplant oncology and pathology. It also talks on future benefits in improving graft and patient survival.
Naruka, et al. [8]	**2022**	**Systematic Review**	This systematic review focuses on cardiac transplantation identifying areas where AI/ML can improve outcomes. Focusing on areas such as mortality prediction, graft failure outcomes and imaging.
Clement, el at. [9]	**2021**	**Traditional Review**	This review focuses on various transplant surgeries, including liver, kidney, and heart. The research here identified three primary uses for AI implementation challenges: bias, AI explainability, and clinical acceptability. This study aims to identify ways to address these challenges.
Schwantes, et al. [14]	**2023**	**Traditional Review**	This review explains the points regarding kidney transplant and how AI/ML improve pre-transplant evaluations, donor selection, and post-transplant management.
Rawashdeh, et al. [15]	**2024**	**Traditional Review**	This study identifies several opportunities for AI in transplantation, including improved donor–recipient matching, outcome prediction, organ allocation optimization, personalized immunosuppression, integration with digital health platforms, and accelerated research, while also considering ethical challenges.
Balch, et al. [16]	**2021**	**Traditional Review**	The primary aim of this study is to review existing research on ML applications in solid organ transplantation. It has a clear focus on how the faces of transplant surgery can be improved using these methods, for example, predict acute post-surgical outcomes like injuries or mortalities. Help patients and doctors with decision-making and mixing data to represent the immune response.
Badrouchi, et al. [17]	**2023**	**Traditional Review**	The reviews aim to help readers better understand AI in nephrology and kidney transplantation. It aims to address how we can learn to use AI to predict graft outcomes and complications, such as delayed graft function. This study also highlights that AI models in kidney transplantation achieve 87% accuracy in distinguishing normal tissue from rejection or injury, suggesting that AI can work alongside a pathologist.
Ramalhete, et al. [18]	**2024**	**Traditional Review**	This study aims to summarize research on kidney transplants and the use of AI and ML. In this study, they use AI to identify donors and manage patients post-operatively. It highlights the potential to reduce organ refusal rates, increase successful matches, and improve graft survival.
Seyahi, et al. [19]	**2021**	**Traditional Review**	This study doesn’t present new statistics but rather summarizes how AI is currently being used for kidney transplant surgery. It focuses on six domains, which include pathology evaluation, prediction of graft survival, and

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			diagnosis of rejection. Prediction of early graft survival, radiologic evaluation of transplanted kidney, and immunosuppressive drug dosing.
Bhat, et al. [20]	**2023**	**Traditional Review**	This study explains how AI, ML, and DL are being used in liver transplantation. The study highlights how models using AI can separate high-risk from low-risk patients. It emphasizes how AI is a better predictor than traditional methods.
Veerankutty, et al. [21]	**2021**	**Traditional Review**	This study reviews how AI is used in a broad spectrum of liver problems and care. It describes how to improve care by AI assisting with imaging, disease detection, surgical planning, and predicting outcomes. AI can also be used to improve imaging interpretation for surgical navigation.
Palmieri, et al. [22]	**2023**	**Systematic Review**	This study overviews how AI contributes to heart transplantation. In the studies used, the authors reported that a common use of AI in heart transplantation was to predict survival after transplant. It also highlights that external validation was not widely used and that this can introduce bias, thereby limiting its usefulness.

Discussion:

In this systematic review, we discuss how AI assists in pre-transplant stages and intra-operative monitoring. We reviewed how AI can specifically improve heart, liver, and kidney transplantation. In addition to discussing the benefits of AI, we report potential challenges surgeons may face when using AI for transplants and explore ways to overcome them.

- *AI in pre-operation and intra-operative monitoring*

All patients undergoing a transplant must undergo a series of pre-operative steps. Within these steps, they must do clinical, social, and financial evaluations to assess eligibility for organ transplant [14]. Once approved, the USA has the United Network for Organ Sharing (UNOS), and Europe has Eurotransplant, both of which are systems that focus on achieving the best donor-recipient matching [3]. As mentioned above, AI was created to imitate specific human tasks; AI has a subclassification called ML, which studies large amounts of data. Since ML encounters more information, it becomes more accurate [23]. Therefore, AI is being implemented to predict organs that are compatible with patients in need. AI is also used to determine where available organs should be distributed based on elements such as inequalities, urgency, and logistical factors [15].

Correct decision-making between patients and doctors is one of the most important parts of successful organ transplantation. Therefore, reliable prognosis information is needed to decide on organ accommodation and clinical settings [16]. Intraoperatively, surgeons can use AI to enhance their decision-making by combining information from electronic records with surgical videos, patients' vital signs, tracking instruments and hands, and monitoring electrosurgical energy usage. Tracking all the data can help surgeons make informed decisions and prevent unwanted events in real-time [2]. Advanced operating rooms would involve both human participants and non-human systems, meaning cognitive processes would extend beyond individual minds [6].

- *Heart Transplantation*

Here, we will discuss how AI using ML or DL can help patients who need Heart Transplantation (HT). AI and ML can predict the advantages of the heart transplant procedure by analyzing lab tests and images, which can determine the likelihood of a graft failing and the patient's mortality after the transplant. AI and ML can help patients find ways to adhere to their medication regimens and promote healthy behavior changes, both of which reduce the chances of future cardiovascular risk [8]. One important standard for evaluating rejection risk is looking at the histopathology of the endomyocardial biopsies. AI has become a key application in studying these biopsies, as manual review of them is very labor-intensive. Using ML shows a promising solution for facilitating these timely clinical actions. [23]. DL can identify characteristics associated with the rejection of the allograft with the help of external human support. It was also observed that post-heart transplant survival was more reliable when the focus shifted from allograft rejection to making better allocation strategies by using ML models [22]. Studies suggest that patients who were allocated to ANN had longer survival post-transplant and shorter wait times [8].

- *Kidney Transplantation*

Results from short-term Kidney Transplants (KT) have improved dramatically since the 1980s due to new advances in surgical methods and immunosuppressives. Nevertheless, there have been no notable advances in long-term outcomes since the early 2000s. As a result, the focus has turned to following kidney transplants to

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predict graft survival and long-term outcomes in patients. ML algorithms can help forecast accurate delayed graft function (DGF), which can help in successful preventive measures [17]. Research has indicated that using the advanced analytical capabilities from distinct ML models, including DL techniques, frequently surpasses the traditional methods for predicting graft survival, therefore improving long-term planning. Management for kidney transplants is based on standardized protocols, resulting in a lack of personalized care. This can lead to patient non-adherence to immunosuppression therapy due to patients facing adverse events or inadequate responses. Applying ML algorithms can help this situation because ML analyzes a wide range of factors that can predict how a patient will react to certain medications. This data can customize therapies to specific needs and make patients complain less [18]. Another helpful tool for transplant is knowing acute renal allograft rejection; ANN offers an accurate early rejection diagnosis. A study made from 100 transplant biopsies demonstrated that using ANN correctly classified 19 out of 21 new cases [19].

- *Liver Transplantation*

In many regions of the world, liver organ distribution is based on the Model for End-Stage Liver Disease (MELD). Initially, the MELD score was used to predict mortality after trans jugular intrahepatic portosystemic shunt, but afterward was authenticated to more population, including hospitalized and ambulatory patients, to forecast 90-day mortality. After a while, the addition of Na was embraced, which became the MELD-Na to help patients undergoing liver transplants assess the threat of death compared to older models. Patients with poor scores for MELD-Na are regarded as having an increased threat of death and are impaired when using this distribution system [20]. The MELD score relies on recipient information based on "sickest-person" guidelines. Certainly, using a method that would consider the characteristics of donors and recipients could help reduce organ loss, lowering the transplant list, which ensures better survival rates after the transplant. ML is being explored to try and address the problem of available organs and the number of patients who need liver grafts [21]. Various studies suggest that using ANNs for liver transplants could help improve patient donor-recipient pairing due to advances in predicting graft survival and loss[3]. Some studies conclude that AI methods have advantages over standard techniques because AI is more capable of being trained and verified across different groups [21].

- *Challenges*

AI is now being employed in the medical field to uncover and forecast specific patterns within given data, aiding in distinct diagnosis processes [24]. Transplant medicine is a complex field, and the need to use immunosuppression medication only introduces extra difficulty. Therefore, we often need computational support like AI for interpretation [16]. AI is not perfect and often faces a few challenges; for starters, when training as a healthcare professional, you learn how to develop empathy and comprehend pain. This can become a dilemma when dealing with AI due to concerns about artificial empathy and how these systems can mimic this empathy and morality [25]. Besides this, AI has not reached full capability due to significant challenges; DL needs substantial amounts of annotated data, which can sometimes be hard during surgery, and ML must be able to operate in real-time to be used in the operating room [26].

Nevertheless, healthcare providers have difficulty trusting ML methods due to their "Black Box" nature [27]. Black Box refers to any AI system whose inputs and operations aren't visible to the user or other interested parties. ML is thriving in the medical field due to its ability to make accurate predictions, often by sacrificing clear-to-understand interpretability, so you typically do not understand the rationale behind the decisions made by the ML model design. People would trust a system that explains where the decisions come from rather than one that doesn't, but sometimes the advantages of the DL black box algorithm are difficult to overlook [17]. Therefore, some studies are testing Explainable AI (XAI) for imagining diagnosing, which can increase clinicians' confidence in making decisions due to the process being more transparent [28].

As mentioned before, ML can analyze substantial volumes of data, which can also highlight one big limitation due to the quality of the input and output data being directly tied. Collecting top-notch data is most important when developing AI models since these models will be trained on datasets essential for algorithms and statistical models [15]. Medicare, pharmacy databases, the Scientific Registry of Transplant Recipients, and some clinical research databases are the existing "big data" repositories available for transplantation. All preferred data points will not be provided within these repositories since they will not provide comprehensive datasets [9]. Additionally, AI models can be influenced by many factors, including the design of the study, the data integration approach, the ML model chosen, and how well that model can work in the specific study [15\]. Evidence also suggests that many patients can't trust doctors who depend on using AI, which can potentially diminish patient confidence and acceptance [9].

Limitations

This systematic review is not exempt from having limitations. Using a limited number of papers to conduct the full systematic review could result in missing some of the necessary information to fully interpret these methods. Another limitation of this review might be the selection of three subspecialty surgeries (heart, liver, and kidney), which may limit the information available on transplantation surgery from other subspecialties. This may result in missing data on advances and challenges that the selected papers may not address. Many of the papers from these studies are already systematic reviews, lacking actual studies, which may lead to biases. No RoB assessment was made, which may also lead to limitations.

Conclusion

AI is rapidly gaining importance in the medical field, especially in transplant surgery. Already used in imaging for diagnosis, AI is now being studied for its role in various aspects of transplantation. New models assist with pre-operative, intra-operative, and post-operative stages. These advances hold promise for improving outcomes and reducing mortality in heart, liver, and kidney transplants. They are helping to improve organ pairing in liver transplant patients and to help determine rejection before surgery in kidney transplant patients. Ultimately, the implementation of specific treatment management for heart transplant patients appears very promising.

Of course, the goal should be to combine all these perks for every transplant surgery, while addressing all doubts and challenges, as AI models often have "black box" warnings. We believe that addressing these challenges can help patients recover quickly and experience fewer side effects. To ensure trust in these technologies, further studies are needed on the use of AI, ML, and ANNs. After sufficient evidence from various specialties, a team should establish clear guidelines for when and how to use these methods. Based on this systematic review, would you consider using AI to improve transplantation surgeries?

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Conflict of interest

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