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Artificial Intelligence and Coronary Artery Bypass Grafting: Current Status and Future Perspectives

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ABSTRACT

Artificial intelligence (AI) is revolutionizing the field of coronary artery bypass grafting (CABG) by enhancing various stages of the surgical process. Pre-operatively, AI, particularly through machine learning (ML) and language processing (LP), assists in consultations, medical diagnostics, and clinical predictions. ML models analyze patient data to predict outcomes and stratify risks, while LP automates the documentation of patient interactions, improving efficiency and reducing recall bias. Intra-operatively, computer vision (CV) plays a crucial role in improving surgical performance and team dynamics. CV can automate surgical checklists, assist surgeons by providing real-time feedback, and enhance procedural accuracy. It also aids in instrument tracking and situational awareness, contributing to better team coordination and reduced intraoperative errors. These applications are particularly beneficial for surgical trainees, offering guidance and improving their technique through real-time analysis. Post-operatively, AI continues to support patient care by predicting complications and optimizing recovery plans. ML models assess the risk of post-operative complications, such as major bleeding, myocardial infarction, and acute kidney injury, based on pre-operative characteristics. This enables personalized patient management and targeted interventions to mitigate risks. Additionally, CV can streamline post-operative processes by monitoring patient turnover and improving operating room efficiency. Despite its potential, the integration of AI in CABG faces challenges, including model overfitting, lack of transparency, and high implementation costs. Ethical considerations, such as patient privacy and data security, must be addressed to ensure responsible AI use. Future research should focus on validating AI applications in real-world settings and exploring their impact on minimally invasive techniques and overall surgical outcomes.

Keywords: Artificial intelligence, coronary artery bypass, computer vision, machine learning, neural networks (computer).

INTRODUCTION

Cardiovascular disease (CVD) is the largest cause of morbidity and mortality worldwide [1]. Life expectancy and disease burden is forecasted to increase over the next 30 years, with a larger focus on non-communicable diseases, leading to an increased number of deaths and disability adjusted life years [2]. CVD has a bidirectional relationship with age and frailty, meaning CVD will be more prevalent as the population ages [3]. Therefore, there is a larger onus on healthcare systems to improve delivery of healthcare, with a focus toward efficiency, and better diagnostics and risk stratification in order to improve outcomes [4].

ARTIFICIAL INTELLIGENCE (AI) IN MEDICINE

Artificial intelligence (AI) as applied to medicine is defined as the use of algorithms to process healthcare data and simulate sentient behaviour to aid decision making and solve tasks [5]. The potential of using AI in healthcare is an emerging topic [4]. However, there is great heterogeneity in the depiction of AI in the literature, therefore, it is important to summarise its main uses as applied to clinical medicine. AI has specific subtypes such as machine learning (ML), neural networks (NN), language processing (LP) and computer vision (CV), each themselves having a vast array of individual techniques (Figure 1).

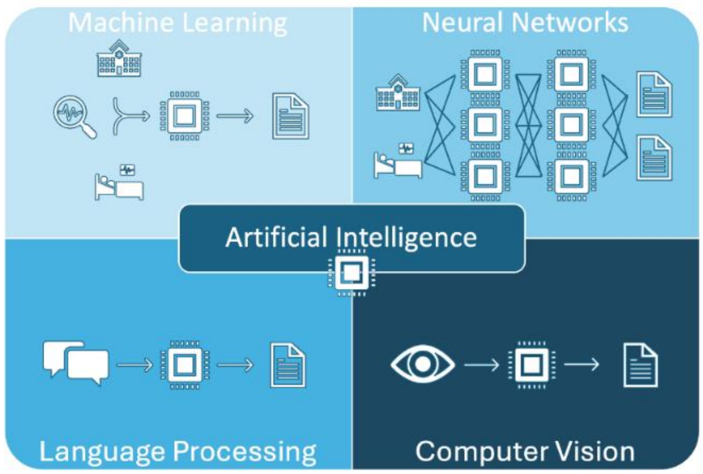

Figure 1: Main types of artificial intelligence with potential use in healthcare.

ML itself is a general term that encompasses a wide variety of computational techniques to process data [6]. ML is a prominent topic within medicine and yet despite its recent popularity, ML techniques have been utilised in studies for many years. ML learning uses data to identify patterns and thus, has been used extensively in prognosis and clinical prediction studies. ML models can either be supervised, where a human inputs the data to 'train a model', or unsupervised, where the model uses unfiltered data [7].

NN is extensively used to order unstructured data to produce classifications to aid with diagnosis and decision making [8]. It can be classified as a further subset of ML, and it aims to emulate brain activity. It can do this by being presented binary data (e.g. positive diagnosis versus negative diagnosis), and devise 'rules' that can aid diagnostic decision making.

LP is a useful tool to consolidate and process large amounts of text or voice data [9]. In an era where data is increasingly granular and utilised for analysis, LP has been used to summarise information from patient notes, treatments and discharges to improve efficiency. LP can also be used for real-time events for documentation to mitigates effects of recall bias e.g. post-procedures.

CV allows the user to process visual data [10]. The use of CV is far-ranging. CV can be used simply to recognise features of images and videos and highlight areas for the attention of the user. CV can be combined with other AI methods, to produce feedback for real-time actions, and therefore can be used to enhance procedural performance of users and team dynamics.

HISTORY OF AI IN MEDICINE

The historical context of AI in medicine traces back to the 1960s, with early attempts to create diagnostic algorithms that laid the groundwork for today's advanced AI systems [11]. The initial exploration of AI in medicine primarily focused on rule-based systems that utilized expert knowledge to diagnose illnesses. One notable example is the MYCIN program, developed in the 1970s, which was designed to diagnose bacterial infections and recommend antibiotics [12]. Although MYCIN was not used in clinical practice, it demonstrated the potential of AI to assist medical professionals in making informed decisions based on data analysis [13]. As computational power increased, so did the complexity of AI applications in healthcare [11]. The introduction of ML in the 1980s marked a significant advancement, allowing algorithms to learn from data and improve their performance over time [11]. This evolution has enabled AI systems to process large datasets, including patient histories, diagnostic information, and treatment outcomes, thereby enhancing diagnostic accuracy and personalizing treatment strategies [11].

Given the broad applicability of AI, the various aforementioned AI methods can be effectively implemented in the pre-, peri- and post-operative setting of cardiac surgery. This article summarises the current literature surrounding the use of AI in surgery, and the potential application to coronary artery bypass grafting (CABG) (Table 1).

Table 1: Benefits of use of artificial intelligence in CABG

Benefit	Description
Enhanced Decision-Making	Provides data-driven insights, reducing biases in clinical decisions.
Improved Surgical Techniques	Analyzes past surgeries to refine techniques and personalize procedures.
Risk Assessment	Uses predictive modeling to evaluate complication risks and improve outcomes.
Minimally Invasive Techniques	Supports robotic-assisted CABG, reducing complications and enhancing recovery.
Training and Education	Generates personalized training materials, improving surgical readiness.

PREOPERATIVE USE OF AI IN CABG

In the pre-operative stage, AI can be used to assist consultations, medical diagnostics and clinical prediction. Through LP, AI can analyse speech from patient and clinician interactions. Recognition and synthesis of large amounts of vocal data takes time to process. Studies have been conducted piloting the use of LP to automatically populate the systemic enquiry between clinician and patient [14]. Furthermore, LP can be used to auto-populate clinic and pre-operative assessment consultations [15]. This would free-up clinician time to perform other important tasks. These records may be less susceptible to the recall bias of clinicians and admin staff, leading to improved record keeping which would have security and medico-legal impact.

AI can be used to in medical diagnostics and risk stratification. Specifically, ML can be

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implemented with be investigations to diagnose medical conditions. ML models require either data to be labelled and inputted by a human into the model (supervised), or alternatively process unlabelled data (unsupervised), as mentioned previously [16]. With radiological investigations, ML can identify patterns and trends. Chest X-rays (CXR) are the most commonly utilised hospital investigation given their accessibility and low cost [17]. They provide insightful information into the status of a patient's lungs, heart and mediastinum, aiding the diagnosis of respiratory and CVD [17]. Combining AI with CXR data has been found to diagnose 8 different pathologies [18]. Furthermore, AI models have been used in echocardiography, performing comparably to sonographers and cardiologists at detecting wall motion [19]. Implementing AI in the investigative arena may act as more of an aid rather than substitute to clinician assessment. It has the ability to signpost clinicians to relevant data that otherwise may not have been identified in an efficient manner, and it can also be used to assist trainees at performing these tasks.

ML learning models have a significant use to predict adverse outcomes in cardiac surgery, with comparisons being made to models derived using classical statistical techniques such as logistic regression [20]. A common pitfall of traditional statistical risk prediction scores such as the European System for Cardiac Operative Risk Evaluation II and Society for Thoracic Surgeons Mortality Risk Score is that they can overestimate risk in specific patient groups (e.g. non-European patients and the elderly) [20]. A meta-analysis of 15 studies by Benedetto et al. showed that ML models were associated with a higher C-statistic compared to logistic regression, and on average were better at mortality prediction following cardiac surgery (20). ML models have an added benefit of the ability to wrangle large volumes of data and improving over time if higher fidelity and quality data is inputted [21]. However, these comparisons to classical techniques are inconsistent and may be less reliable due to model instability and lack of methodological reproducibility.

INTRAOPERATIVE USE OF AI IN CABG

AI, and CV specifically, has utility to improve theatre team dynamics and boost intraoperative performance. Firstly, a simple implementation of CV is for simple surgical checklists. Routine implementations prior to surgery to improve safety such as WHO checklists can be automated and completed by the theatre team using CV. CV can display such checklists and assist the team for completion. Additionally, CV can be used throughout a surgical procedure to assist the surgeon as an individual and within a team. Individually, particularly in the context of surgical trainees, CV can assist a surgeon through each surgical phase [22]. For instance, senior surgeons can visibly mark positions, features of anatomy and potential weaknesses in a trainee's technique in real-time [22]. However, CV's ability to identify surgical phases may still be inferior to surgeon identification [22]. Finally, CV can also be used for automated instrument counts in the operating room environment, particularly with the proposal of RFID identification of surgical instruments [23]. Whilst the majority of CV for these purposes has been studied in general surgery, routine applicability to support the surgical process in coronary surgery has potential [24,25].

Secondly, CV can assist surgeon technique [25]. Surgical technique can be quantified using a variety of data including idle time, task completion time, number of movements and rate of change of tool orientation [25]. Surgical expertise therefore can be improved by optimising such parameters to improve surgical proficiency and efficiency [25]. CV can be utilised to assist and improve surgeon performance through analysis of intra-operative kinematic data [25]. In some cases, analysis of CV gathered information performed better than analysis conducted by experts [26]. Recent data has demonstrated improved technique by using CV in simulated graft anastomosis [27]. However, there are no real-world studies published in this area of cardiac surgery.

Thirdly, CV can improve theatre team performance, particularly through analysis of situational awareness. Improved team dynamics leads to better patient outcomes and lower frequency of errors [28]. A study from Dias et al. used CV in conjunction with a validated tool to assess situational awareness through observation [29. They were able to distinguish good situational awareness from poor situational awareness amongst theatre teams through CV analysis of body positions and motion patterns [29]. Such implementation has a potential to reduce intraoperative complications and can also facilitate education where theatre teams can reflect and optimise performance [28].

LP can be used as a powerful tool in surgery to provide a comprehensive record of procedures to improve quality and patient safety [30]. Goldenberg et al. termed this use as the "black box" of the operating room, allowing the theatre team to learn from real-time data that produces a procedural timeline [30]. Data from surgeries can be processed using LP to assist theatre documentation which can be subject to recall bias from the documenter [30]. This could be applied to coronary surgery specifically, where there is a high capacity for complications to occur.

On a wider level, research using ML models have been conducted to predict workflow in theatres based on patient operating times and risk of complications. Integrating ML methods to predict delays and optimise turnover times could lead to cost savings [31].

POSTOPERATIVE USE OF AI IN CABG

Cardiac surgery patients are susceptible to severe in-hospital and post-discharge complications. Common complications include, major bleeding, post-operative myocardial infarction, return to theatre, acute kidney injury, and all-cause mortality. Therefore, it is pertinent to stratify patients by their risk of these complications and implement strategies to mitigate risks e.g. pre-rehabilitation and tailored pre- and post-operative management of comorbidities amd frailty [32].

ML has been commonly used to assess post-operative outcomes when considering pre-operative characteristics. However, ML models face scrutiny [33]. The performance of any model is dependent on the quality of the data that is inputted [33]. Therefore, it is recommended that ML models are supervised by expert clinicians or used in conjunction with classic logistic regression models. Applied to cardiac and coronary surgery, prediction models have been developed to assess a patient's risk of post-operative complications following off-pump CABG [34,35]. This has been extended to prediction of severe complications up to 90-days following discharge using supervised ML techniques [35,36]. Furthermore, proof-of concept studies utilising ML for the interpretation of pathology specimens has shown promise, although no studies have been conducted using cardiac specimens, which could be explored [37].

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Finally, CV could be used for theatre room efficiency. Simple implementation such as monitoring when drapes are removed from patients in order to automatically signpost the Intensive Care Unit and cleaning crews toward patient turnover could be effective [38]. When used in conjunction with ML models to predict operation times and risk of complications, there are significant cost-saving implications [30,31,38].

FUTURE PERSPECTIVES

The AI methods outlined above may have a significant impact to support the future of coronary surgery. NN have been used to detect vessel occlusions on CT angiography for suspected stroke patients in under 2 minutes, yielding 97% sensitivity and a 93% negative predictive value [39]. However, applicability to CT coronary angiography is a potential that has not been robustly explored.

Recently, there has been a shift toward using minimally invasive techniques in cardiac surgery, with multiple trials conducted attesting to its non-inferiority over conventional open surgery [40,41]. CV has been studied in endoscopic general surgery, where it has been proposed to grade surgical technique to improve surgical skills training [42].

More studies need to be conducted investigating the use of AI in CABG and cardiac surgery in general. Current evidence is sparse and has not been reproduced at other centres, which inhibits evidence based uptake of AI in surgery. Randomised studies into the use of CV to assist surgical training and techniques, and more broadly to investigate improvements of theatre efficiency using AI, could be promising.

CHALLENGES AND LIMITATIONS

Aspects pertaining to the limitations of implementing AI have been mentioned previously (Table 2). Briefly, the main promise of AI has been the utilisation of ML learning in large datasets for clinical prediction. A limitation is the tendency for overfitting of models to provide the best model, and the development of models that lack stability [43]. Furthermore, there is ambiguity in the methods underpinning AI techniques. In classical statistical modelling, there is traceable input and mathematical understanding at each stage, leaving little to interpretation as the methods should be reproducible if another dataset is used to externally validate data. However with AI, there are no discrete ways to trace an algorithm’s decision making process, meaning by extension, there is a lower degree of reducibility. This has challenges for implementation as models are less able to be externally validated and implemented with confidence. If an adverse event were to occur due to AI, a route cause analysis would be difficult due to our current lack of ability to understand the decision making processes underpinning AI. Finally, as healthcare systems shift toward digitalisation, the cost of implementing additional structures using AI can be costly. In particular, valuable data stored digitally is susceptible to be mismanaged, targeted and stolen [44]. This has major cost ramifications to improve security in the storage, distribution and use of sensitive patient data [45].

Table 2: Challenges and limitations of use of artificial intelligence in CABG

Challenge/ Limitation	Description
Ethical Considerations	Ensuring AI systems maintain patient trust and safety.
Algorithmic Transparency	Difficulty in understanding and tracing AI decision-making processes.

Data Quality and Bias	Reliance on high-quality, representative data to avoid inequitable outcomes.
Regulatory Challenges	Need for robust guidelines to ensure ethical standards and compliance.
Continuous Adaptation	Ongoing monitoring and adaptation to new challenges and ethical dilemmas.

The integration of AI in healthcare raises critical ethical challenges, including concerns about patient privacy, data security, and the potential for biased decision-making [46]. As AI continues to evolve, the healthcare industry must navigate these ethical complexities to ensure that patient care remains at the forefront of technological advancements [46]. As AI systems play a larger role in clinical decision-making, it becomes essential to ensure these systems are transparent, explainable, and accountable to avoid unjust biases in patient care. For instance, the development of Responsible AI systems is crucial for addressing issues such as informed consent, safety, algorithmic fairness, and data privacy [47]. As AI is increasingly utilized in patient pathways and surgical outcomes, regular exchanges between stakeholders will facilitate the identification and resolution of ethical dilemmas arising from AI integration in surgical settings [48]. Inadequate regulatory frameworks may lead to instances of "ethics washing," where companies superficially address ethical concerns without meaningful compliance or accountability [48]. Therefore, it is essential that embedded ethics is integrated as a core component of technological development rather than as a form of self-regulation within the industry [48].

CONCLUSIONS

In conclusion, AI comprises of a variety of subgroups of techniques (NN, LP, CV and ML) that can be applied to coronary surgery in the pre-, intra- and post-operative setting (Table 3).

Table 3: Key applications of artificial intelligence in different stages of CABG

Application Stage	AI Technique	Description
Pre-operative	Machine Learning (ML)	Predicts patient outcomes and stratifies risks based on pre-operative data.
	Language Processing (LP)	Automates documentation of patient interactions, improving efficiency and reducing recall bias.
Intra-operative	Computer Vision (CV)	Enhances surgical performance through real-time feedback, automates surgical checklists, and assists in instrument tracking.
	CV & ML	Improves situational awareness and team dynamics, reducing intraoperative errors.
Post-operative	ML	Predicts complications and optimizes recovery plans, aiding in personalized patient management.
	CV	Monitors patient turnover and improves operating room efficiency.

Many studies utilising AI have been applied in simulated environments or in other surgical disciplines. However, the potential to implement these techniques in coronary surgery is still to be explored. Future work is required to investigate how these techniques can be applied to coronary surgery specifically, and whether the potential benefits of implementing novel AI-driven care is worth the investment and inherent risk data-driven healthcare incites. To realize

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the full potential of AI in CABG, interdisciplinary collaboration among ethicists, clinicians, data scientists, and policymakers is essential. This collaboration can foster an environment where ethical considerations are embedded within the development process of AI technologies. As AI is increasingly utilized in patient pathways and surgical outcomes, regular exchanges between stakeholders will facil- itate the identification and resolution of ethical dilemmas arising from AI integration in surgical settings.

Author Contributions

BSS: Conceptualisation, Writing – original draft. SGR: Conceptualisation, Writing –original draft, Writing – review & editing. Both authors read and approved the submitted version.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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