Table 1: Summary of Individual Sources

Project Topic	Artificial Intelligence for *Optimized* Prioritization of Outpatient CT Scans at Princess Margaret Hospital			
In-text citation	What was the Research question/ objectives / were addressed in the article?	What research method was used to investigate / evaluate the problem?	What were the key learning about the actors, context, and/or intervention success/failure to take from this article?	How does this article inform the development of your project?
(Yong Su Lim et al., 2025)	The article evaluated whether an AI-driven software, Heuron ELVO, which utilizes non-contrast CT (NCCT) scans to detect large vessel occlusion (LVO) strokes and provide automatic triage/notification, can reduce treatment times and improve clinical outcomes.	Quantitative methods were used. This was a retrospective before-and-after study, in which the final analytical sample comprised 82 participants in the pre-AI cohort and 48 participants in the post-AI cohort. Patient data from a comprehensive stroke center was analyzed to compare treatment times and clinical outcomes before and after the implementation of the AI tool. Key metrics such as door-to-treatment times and stroke severity scores were collected to evaluate the AI tool's impact on	The implementation of an AI tool for this clinical site meaningfully reduced treatment delays and improved patient outcomes. Door-to-CT times did not show a significant difference; however, the substantial reduction in CT-to-EVT (endovascular therapy) times suggests that the integration of Heuron ELVO has an enormous impact on the most time-sensitive part of the stroke care pathway. Successful implementation relied on straightforward integration with existing clinical workflows and effective communication between human and machine actors .	This article informs the development of our project by demonstrating how AI tools can significantly improve triage workflows in time-critical clinical settings. However, this tool had dual applications: diagnostics and optimization, which need to be considered. Similar to our project, the AI system in the study was designed to optimize the speed and efficiency of triage for a specific disease by rapidly identifying potential significant vessel occlusion cases from standard imaging and alerting the clinical team. The result was faster treatment times and improved patient outcomes through the prioritization and escalation of care more efficiently after diagnosis.

		stroke management and outcomes.		Importantly, both this study and our project are focused on implementation within a single clinical site. This single-site focus enables more detailed observation of how triage processes change in practice, and the appropriate KPIs to consider in the context of the ailment being addressed when designing metrics and criteria for the rubric.
(Topff et al., 2023)	The study aimed to determine whether an AI tool for automatic detection and worklist prioritization of incidental pulmonary embolism (IPE) on CT scans could reduce the time to diagnosis compared to routine workflows and human triage. It also sought to evaluate the AI's diagnostic accuracy and its impact on radiology workflow efficiency.	This was a retrospective cohort study analyzing CT scans from oncology patients. The AI tool was applied to historical CT data, and diagnosis and notification times (DNT) were compared across three workflows: routine, human triage, and AI-enabled triage. The sensitivity, specificity, and overall diagnostic accuracy of the AI tool were also evaluated.	The AI tool significantly reduced median diagnosis and notification time, from thousands of minutes in routine workflows to under 90 minutes, while maintaining high sensitivity (91.6%) and specificity (99.7%). This demonstrates reliable and effective prioritization that can improve patient safety by reducing delayed or missed diagnoses.	Although the study focuses on AI-enabled diagnostic prioritization rather than scheduling, it provides valuable insights for developing our project. It highlights the importance of accurate, reliable prioritization algorithms that can process complex clinical information quickly and consistently. This is largely influenced by the quality of the data that we input into the model and the standards set for the ground truth
(Ho et al., 2022)	Their objective was to apply a Lean Kaizen quality-improvement	This project fits more under quality improvement (QI) rather than a research	The study authors highlight that the Lean Kaizen QI model was successful in this setting,	When optimizing CT scan scheduling with AI, it's crucial to first understand and improve

	intervention to the scheduling workflow (between oncology clinic, radiology, scheduling, administration) with the goal of substantially reducing the percentage of CT scans overdue for scheduling. Specifically, they set to redesign the workflow in the clinic such that they achieve a target of decreasing the overdue scheduling rate to below 20%	project. For this process, they looked at before and after improvement interventions to see how it works: 1) conducted a series of structured, interdisciplinary meetings (radiology, oncology, scheduling, administration) to "critically review" the current scheduling process and apply Lean/Kaizen methods. 2) developed a new workflow: clinic staff schedule CT scan before clinic discharge instead of leaving scheduling until later. 3) After a three-month planning period, they launched the new workflow. They measured baseline data (75	demonstrating that a relatively modest operational change (workflow redesign + scheduling at clinic) can yield large improvements, given the right conditions. A key factor that facilitated their success was the implementation of inter-departmental collaboration and continuous monitoring for the improvement to work.	existing workflows, as the Lean Kaizen study shows that even simple process changes can dramatically reduce delays. In addition, this project gives us good context on how to approach this project from a QI perspective instead of a strict research view. Unlike traditional research, quality improvement focuses on practical, iterative changes in real-world settings with active staff involvement and continuous monitoring. In addition, this paper highlights the importance of understanding the scope and tactual impact that AI can make; AI excels at handling complex scheduling variables, predicting no-shows, and automating communication, but it can't solve organizational barriers, resource shortages, or staff resistance. These are areas where workflow redesign and human collaboration remain essential.

		CT scans awaiting scheduling, 87% overdue) and then measured data at 5 weeks (53 scans: 17% overdue) and at 10 weeks (103 scans: 0.97% overdue		
(Roussos et al., 2017)	This paper presents the results of an audit conducted for the patient schedules for a CT simulation within the Radiation Medicine program at Princess Margaret Cancer Centre. The Audit was developed so that they could understand which areas could be explored for improved efficiency and decreasing wait times.	The authors use a mixed-methods approach, combining retrospective data analysis, stakeholder interviews, and quality improvement initiatives to investigate current bottlenecks and implement process adjustments.	The success/findings from this article were mainly attributed to the interventions employed in the simulation: Interventions such as prioritization protocols, enhanced communication channels, and schedule adjustments successfully reduced simulation wait times. However, challenges still arose when it came to managing patient urgency, and balancing routine vs. urgent cases, because there is a lack for clear criteria and real-time scheduling flexibility.	This paper is relevant to our project in that it highlights a similar problem scope that is seen at the same institution (PM) under a related department (Radiation). It reinforced the importance of having an accurate urgency classification system and showed again areas where AI could improve that traditional implementations lacked. It suggests potential integration points where the AI system can support the prioritization workflow and provides insight on how a simulation can be used to assess the efficacy of the model.
(Al Harbi et al., 2024)	The study investigates the effectiveness of implementing a	The authors conducted a pre-post intervention study at a single center, analyzing	The process mapping and standardization led to clearer criteria for prioritizing urgent	The use of standardized prioritization and communication protocols aligns

	structured quality improvement (QI) initiative aimed at reducing delays in CT imaging for oncology patients. The primary objective is to assess whether the introduction of standardized protocols and process enhancements can improve the timeliness of CT scan appointments within a clinical setting.	CT scan wait times before and after the implementation of the QI project. The intervention used Lean methodology and Plan-Do-Study-Act (PDSA) cycles to identify process inefficiencies and test changes. The intervention included mapping the patient referral and scheduling workflow, standardizing communication protocols between oncology and radiology teams, and introducing checklists and prioritization criteria for urgent cases. Data on wait times were collected from hospital records, and staff feedback was gathered through surveys and interviews to assess process acceptability and barriers. The study used descriptive statistics and run charts to evaluate changes over time.	CT scans, resulting in statistically significant reductions in wait times. The study highlights the importance of continuous feedback and iterative testing through PDSA cycles to refine interventions. Barriers encountered included initial resistance to change and communication gaps, which were mitigated through regular multidisciplinary meetings and leadership support. The context of a busy oncology imaging service with competing demands shaped the intervention's focus on workflow clarity and communication efficiency.	well with our goal to produce transparent and actionable AI outputs that clinics can trust and act upon. Furthermore, the success of the PDSA cycles highlights the importance of continuous evaluation and adaptation throughout the project's development. Addressing resistance and ensuring buy-in through multidisciplinary collaboration was also a good potential barrier that was noted, which informs our strategies later on in the project that need to be developed to support user engagement and training.
(Din et al., 2025)	The study aimed to explore clinicians' attitudes, perceptions, and concerns regarding	The research employed a qualitative methodology using semi-structured interviews or focus groups	Clinicians generally expressed cautious optimism about AI triage tools, recognizing their potential to improve workflow	This article emphasizes the importance of designing the AI tool with transparency and clear rationales to build trust among

	the implementation of artificial intelligence (AI) systems to assist in triaging MRI brain scans. Specifically, it investigated how clinicians perceive the usefulness, reliability, and ethical implications of AI tools in prioritizing urgent cases and streamlining imaging workflows.	with clinicians (radiologists, neurologists, or other relevant specialists). Thematic analysis was applied to the interview transcripts to extract key themes reflecting clinicians' perspectives on AI-assisted triage.	efficiency and reduce wait times for urgent MRI brain scans. Concerns were raised about the reliability and accuracy of AI outputs, emphasizing the need for transparency and explainability in AI decision-making. The success of AI integration depended heavily on user trust, adequate training, and seamless incorporation into existing workflows.	users, particularly non-clinical administrative staff who may rely on AI outputs for triage decisions. While the project focuses on supporting administrative rather than clinical users, the insights into reliability, explainability, and ethical considerations remain crucial. The findings suggest that incorporating user-friendly explanations and ensuring the AI acts as a decision-support tool will facilitate adoption and effective use during blitz shifts. Additionally, addressing concerns around data privacy and bias will strengthen the project's credibility and operational acceptance.
(Knight et al., 2023)	The article aimed to systematically summarize up-to-date evidence on the application of artificial intelligence (AI) and machine learning (ML) models for scheduling optimization in clinical settings. The review focused on real-world applications of AI/ML in healthcare scheduling and reported	The authors conducted a systematic search across multiple databases up to August 2020 to identify studies describing real-world applications of AI and ML in healthcare scheduling. The studies included were those that utilized AI/ML models to optimize patient scheduling processes in real-time clinical settings. The	The study identified significant delays in the scheduling process, particularly in the pre-examination phase. Factors contributing to these delays included administrative inefficiencies, lack of standardized procedures, and insufficient communication between departments. The findings highlight the need for streamlined workflows and improved coordination among	The review confirms that scheduling in healthcare is a recognized challenge and that AI/ML has already been applied to scheduling optimisation in real world clinical settings. It documents that delays, especially in the pre-examination phase, stem from administrative inefficiencies, lack of standardised procedures, and poor inter-departmental

	outcomes such as workload, burden, burnout, cost, utilization, patient and provider satisfaction, waste reduction, and quality.	outcomes of interest were assessed across various stakeholders, including providers, patients, and health systems. Both qualitative and quantitative studies were included to assess outcomes such as efficiency, satisfaction, and operational impact.	healthcare providers to enhance scheduling efficiency.	communication. The review summarises diverse outcomes from studies of scheduling optimisation: e.g., reductions in wait-time, improved utilisation, decreased no-shows or missed appointments, improved provider and patient satisfaction, and reduced waste. The article highlights that the priority for a successful model integration is having goals tailored towards improvements that are not only technical (algorithmic) but also organisational, considering stakeholder engagement, workflow redesign, and communication. This means that the tool should not simply output a priority score. For it to succeed, we must consider how schedulers, clinicians, and administrators will use, trust, and integrate the output into their workflows, creating minimal friction. In addition,

				To improve chances of adoption, we must be articulating clearly how the tool supports institutional priorities (e.g., meeting clinical timelines, reducing delays, freeing up coordinator time, improving patient experience). Also, because AI scheduling tools often shift rather than eliminate bottlenecks, we should plan for monitoring across the system (not just scheduling) and engage stakeholders early to understand workflow implications.
(Almanaa et al., 2024)	The study aimed to assess the efficiency of MRI and CT scan scheduling workflows in two major government hospitals in Saudi Arabia by analyzing the time intervals from physician request to exam execution.	The authors conducted a retrospective quantitative analysis of scheduling data spanning five years at two large hospitals. They examined timelines from referral receipt to imaging completion, identifying workflow bottlenecks and variations in scheduling efficiency. Statistical analysis was used to quantify delays and pinpoint process gaps.	The study revealed there were delays in the administrative scheduling phase, with non-standardized workflows and communication gaps between departments prolonging wait times. It highlighted that administrative staff play a key role but are hindered by fragmented information and manual processes. The context of large, complex hospital systems showed how	This article underscores the importance of efficient scheduling workflows in reducing patient wait times and improving service delivery. It informs the project by highlighting the need to identify and address bottlenecks in the scheduling process and use scheduling times as the standard for classifying urgency in imaging requests, since they are easily translated and

			operational inefficiencies at multiple levels compound scheduling delays.	understood well in the clinical and administrative context.
(Paudyal et al., 2023)	The article reviewed how artificial intelligence (AI) is being applied to CT and MRI in oncological imaging, and it sought to identify both opportunities and key challenges in translating these AI tools into routine clinical and workflow practice.	The authors conducted a narrative review of the literature (2018–2022) on AI applications in CT and MRI for oncology: they summarized narrow-specific tasks (e.g., segmentation, reconstruction, image quality) and discussed the barriers to integration into clinical workflows.	(1) AI tools show strong promise in narrow imaging tasks (auto-segmentation, image reconstruction) but integration with real-world workflows remains weak. MDPI (2) Success depends on collaboration between radiologists, clinicians, physicists, vendors and administrative teams to ensure that image data, protocols and workflow context are aligned. PMC (3) Without streamlined clinical workflows, reliable quantitative biomarkers, standardization and trust, tools risk low adoption despite technical accuracy	The study provided good information about the common barriers that stop study-backed AI tools for clinical tasks from having realistic deployment. It informs the considerations that we need to take as the tool is deployed (i.e., *enter information here*) and how priority should be given to rigorous validation and proper training before adoption in care. Even though this study highlights these considerations within the context of activities more clinical focused(e.g., diagnostics, risk assessment.
(Canadian Association of Radiologists, 2013):	The main objective of the document was to establish national maximum wait time targets for MRI and CT imaging across Canada. It	The authors conducted a systematic literature review to identify evidence linking imaging wait times to patient outcomes, though no studies met their	Key learnings include the recognition that radiologists, referring physicians, and health administrators all play crucial roles in managing imaging access. The context	This article directly informs the project by providing a validated prioritization framework (P1–P4) and shows that wait time benchmarks informed by these prioritizations should be

	aimed to standardize the definitions, priority levels (P1-P4), and measurement methods for wait times to ensure consistency across provinces and territories. The document also sought to guide data collection, reporting practices, and clinical prioritization in order to improve access to diagnostic imaging and reduce variability in care delivery.	criteria. Due to the lack of strong evidence, the final recommendations were developed using expert consensus methods. This involved consultation with an expert panel and a national consensus group of radiologists through surveys, teleconferences, and stakeholder feedback, using a modified Delphi process to finalize the guideline.	revealed a lack of standardized data collection and reporting processes, contributing to inefficiencies and unequal access to imaging services. While the intervention (i.e., establishing national targets and definitions) was a success in creating a uniform framework, its effectiveness depends on consistent adoption across jurisdictions. A limitation was the absence of strong evidence linking wait times to health outcomes, highlighting a need for further research. The lack of real-time prioritization tools and system-level data tracking remains a major barrier.	the focus/output for criteria development instead of this framework. The emphasis on standardized metrics and definitions supports the tool's ability to flag discrepancies and ensure consistent triage. Importantly, it confirms that the project addresses a recognized national problem (i.e., CT wait time delays) that needs consideration on a local level, especially since each clinic has specialized needs. In addition, it highlights the scarcity of literature available that informs the current landscape of scheduling four outpatient scans on a global level, with even less being available on the national scale.
(Fraser Institute, 2024)	The primary question the report addresses is: How long are Canadians waiting for medically-necessary health care (including diagnostics and treatment) from referral to specialist to treatment,	Quantitative methods were used. The Fraser Institute's 2024 "Waiting Your Turn" report used a national physician survey as its primary research method. Specifically, it surveyed specialist physicians across 12 medical specialties and all 10 Canadian provinces.	The Fraser Institute's 2024 report shows that Ontario has one of the shortest wait times in Canada, yet still exceeds clinically recommended benchmarks. The median wait time from GP referral to treatment in Ontario is 23.6 weeks, while patients wait a median of 6.0 weeks for a CT	The report addresses a long-standing and underlying issue that contextualizes the problem space that we are addressing: long wait times. By understanding the root-cause of the issue we are addressing, we are better informed of the scope of impact this AI tool can have, encouraging us to focus

	and how do wait times vary by specialty, diagnostic modality, and province?	Respondents provided estimates on wait times between GP referral and specialist consultation, as well as from consultation to treatment. The 2024 edition received 1,973 physician responses, representing a 17% response rate. This self-reported data was used to calculate median wait times and assess trends across regions and specialties.	scan and 12.8 weeks for an MRI. Despite being lower than the national averages (8.1 weeks for CT and 16.2 weeks for MRI), these delays remain significant, especially for patients requiring timely diagnosis to guide urgent treatment decisions. These delays have serious consequences for patients, including prolonged pain, anxiety, and risk of disease progression while waiting for diagnosis or treatment. They also impose broader economic costs, with an estimated $3.9 billion in lost productivity due to patients being unable to work while awaiting care. The report points to systemic issues, such as insufficient diagnostic capacity, growing demand, and inconsistent provincial resource allocation as key contributors to the ongoing wait time crisis in Canada's public healthcare system.	on optimization methods and notification systems for the solution, rather than building a solution that tackles a long-standing national problem. It also highlights how the other features of this tool can be expanded to potentially address information gaps regarding CT scheduling wait times. The report informs us that providing insights that better inform the larger problem space of long wait times, may give a better context, inspiring solutions that hadn't otherwise been considered. In addition, the report highlights how this root-cause problem has been affected by external factors like the pandemic. Having this context helps us understand the rate at which the problem has exacerbated and informs again the most practical scope that an AI tool can tackle for this problem space. Prior research/specialized focus on what the cost/impact is for

				outpatient CT scheduling in particular would have been helpful to have
(Szekeres et al., 2025)	The study identified and addressed a significant outpatient CT scan backlog at the University of Rochester Medical Center, where average scheduling intervals had increased from 2 to 6 weeks in 2022 due to rising demand and staffing challenges. The research objective of the article) was to reduce the outpatient CT scheduling interval at the University of Rochester Medical Center from 6 weeks to 10 days by January 2023.	The research employed a Lean Six Sigma quality improvement framework to evaluate and address delays in outpatient CT scheduling. The team first mapped the existing scheduling workflow using a value stream flowchart and identified root causes of delays through an Ishikawa (fishbone) diagram, involving key stakeholders such as radiology technologists, nurses, schedulers, and radiologists. Baseline data on scheduling intervals were collected over a year to quantify the problem. The team then implemented a series of targeted interventions sequentially, starting with temporary double-booking of appointment slots, shortening exam durations,	The article emphasizes that strong collaboration among various stakeholders, radiology technologists, schedulers, radiologists, and nursing staff, was essential for identifying the root causes of scheduling delays and successfully implementing improvements. Their engagement and buy-in played a critical role in the initiative's success. The study took place in a context of increasing outpatient CT demand and staffing shortages, which created bottlenecks in scheduling and scanning capacity. These challenges shaped both the choice of interventions and their effectiveness. Key measures such as temporary double-booking rapidly reduced the scheduling backlog by 72%, while shortening exam times and adding an additional CT scanner further decreased	First, it reinforces the importance of addressing systemic bottlenecks in diagnostic imaging access through targeted, context-specific interventions. While the research team achieved success by increasing scanning capacity (e.g., double-booking, shortening scan slots, adding equipment), they also highlighted that some inefficiencies are rooted in the scheduling process itself, not just the availability of machines. Our project builds on this by focusing upstream: optimizing which patients are booked first, rather than only when or how many are scanned. By using AI to automate urgency stratification based on clinical data, we aim to introduce smarter prioritization into existing scheduling workflows. Second, the article emphasizes stakeholder engagement and iterative implementation, key

		adjusting staffing shifts, and adding an additional CT scanner. Each intervention's effectiveness was tracked using control charts that monitored the average scheduling interval and appointment delays as balancing measures. Staff feedback was also collected to assess subjective impacts.	wait times, achieving the goal of under 10 days. Despite these improvements, some limitations persisted. Appointment start delays remained unchanged, and report turnaround times increased, indicating new workflow bottlenecks. Although staffing shift adjustments were well received, they did not significantly impact scheduling intervals. The study also highlights the importance of sustaining improvements over time and suggests future directions including patient-driven scheduling, urgency-based prioritization, and assessing the appropriateness of imaging orders to better manage demand and improve equity.	principles we are integrating into our development. Like the Rochester team, we are designing our tool with direct input from referring physicians, patient flow coordinators, and radiologists to ensure clinical relevance, workflow compatibility, and user trust. Finally, the study shows that improvements in one part of the system (e.g., scheduling) can create downstream challenges (e.g., reporting delays). This highlights the need for balanced system-wide thinking in any intervention
(Cadth, 2023)	The article aims to summarise and assess existing wait-list strategies for CT and MRI scans in Canada. More specifically, it seeks to identify and describe the	This work is a health-technology or policy review rather than primary experimental research. The authors compile published literature, policy documents and	The review highlights that imaging facilities, referring physicians, scheduling/booking services, health-system planners and provincial ministries play important roles in managing	This article provides a strong evidence base for the need to improve CT/MRI access through strategy and process, not only hardware (though hardware does relieve a lot of the burden). It also emphasises

	approaches provincial and territorial systems have used to manage demand, improve scheduling and intake, and reduce waits for these diagnostic imaging modalities.	inventory/registry data on diagnostic imaging wait times, imaging capacity and existing interventions (e.g., central intake, triage, prioritization). It synthesises secondary data (e.g., from the Canadian Medical Imaging Inventory) and documents strategies used across jurisdictions.	waits for CT/MRI. It shows that the current landscape is one of rising demand for imaging, limited capacity (equipment and technologists), and significant variation in access within provinces. Among the findings: simply increasing equipment alone is insufficient; workflow, referral patterns, intake and scheduling processes matter. Some interventions succeed when they combine capacity, process change, and prioritization; but many jurisdictions still face long waits, indicating structural failures or incomplete implementation.	stakeholder engagement (referring clinicians, booking staff, imaging services) and the value of analysing and modifying workflow. This review supports the rationale that while this is a project aimed at one portion of the workflow for patient flow coordinators, it should be able to integrate with existing systems tackling clinical urgency stratification, scheduling optimization, and workflow improvement to address the wait-list problem effectively.
(Momin et al., 2025)	Does deep-learning worklist triage actually reduce diagnostic delays (like report turnaround time) and improve clinical outcomes across different imaging settings?	Systematic review of primary studies on DL-based radiology worklist optimization from 2018 to 2024.	DL worklist triage consistently shortens report turnaround time across different diseases. The most significant improvements happen in higher-prevalence or lower-acuity settings. How well it's integrated into PACS/RIS and the alerting system really matters for actually getting benefits from it.	This supports the use of AI to reprioritize outpatient CT queues for suspected time-sensitive oncology cases. We'll see the most significant wins where volumes are high and acuity is moderate, as long as integration and notifications work smoothly. It also defines outcome metrics (report turnaround time, time-to-action) that we can use for our project.

(Tyler et al., 2024)	What's the role and effectiveness of AI for clinical triage across hospital settings (diagnosis, severity, and urgency determination)?	Narrative review of AI triage applications in hospitals (ED and inpatient), summarizing diagnostic and prioritization impacts.	AI triage can enhance the recognition of urgent conditions and aid in prioritizing care pathways. However, governance, monitoring for data drift, and human oversight are essential for safety.	This supports the implementation of an AI-assisted prioritization service for CT, with explicit oversight (starting with shadow mode, then pilot, followed by an appeals path and monitoring dashboards). It highlights that we need to track fairness and safety as part of governance.
(Pierre et al., 2023)	How can machine learning streamline radiology operations (wait-time prediction, appointment delays, no-shows) and what evidence exists for workflow optimization benefits?	An integrative review in Seminars in Nuclear Medicine summarizes the applications of ML across operational bottlenecks.	ML can accurately predict wait times, delays, and no-shows, which allows you to manage slots and conduct targeted outreach proactively. Combining predictive models with scheduling rules enhances throughput and improves the patient experience.	We could pair clinical-urgency ranking with no-show risk to efficiently fill scarce CT slots (similar to dynamic overbooking or tailored reminders) and measure both timeliness and utilization.
(Abdalhalim et al., 2025)	What clinical impact do AI-based triage systems have in emergency departments (throughput, accuracy, safety)?	Systematic/narrative review of ED AI-triage studies and outcomes.	AI triage can improve ED efficiency, but multi-centre validation, standardized reporting, and oversight are critical.	This reinforces our plan to implement shadow mode first, followed by a pilot, with governance/appeals and standardized metrics in place before full CT-booking deployment.
(Buijs et al., 2024)	What's the clinical impact of AI across radiology department management - like no-show prediction,	Narrative review summarizing departmental-level outcomes from AI deployment.	AI enhances forecasting for complications and no-shows, facilitates more accurate economic reporting, and can	This emphasizes the need to pair operational KPIs (utilization, overtime, cancellations) with clinical timeliness outcomes in our

	resource planning, and economics?		increase throughput when integrated into routine operations. Change management and getting stakeholder buy-in are critical for success.	Princess Margaret CT prioritization dashboard. We also need structured change management with booking staff and radiologists to make sure everyone's on board.
(Yong Su Lim et al., 2025)	The article examined whether Heuron ELVO, an AI-driven software that utilizes non-contrast CT scans to detect large vessel occlusion strokes and automatically triage/notify, can reduce treatment times and improve clinical outcomes.	They used quantitative methods in a retrospective before-and-after study. The final sample included 82 people in the pre-AI group and 48 in the post-AI group. They analyzed patient data from a comprehensive stroke center to compare treatment times and clinical outcomes before and after implementing the AI tool. They collected key metrics, such as door-to-treatment times and stroke severity scores, to evaluate how the AI impacted workflow efficiency.	The AI tool meaningfully reduced treatment delays and improved patient outcomes at this clinical site. Door-to-CT times didn't change significantly, but the significant reduction in CT-to-EVT (endovascular therapy) times shows that integrating Heuron ELVO had a substantial impact on the most time-sensitive part of stroke care. Success came from straightforward integration with existing workflows and effective communication between human and machine actors.	This study shows how AI tools can significantly improve triage in time-critical clinical settings. The tool had dual applications, though - diagnostics and optimization - which we need to think about. Similar to our project, the AI system was designed to optimize stroke triage speed and efficiency by quickly identifying potentially significant vessel occlusion cases from standard imaging and alerting the clinical team. The result was faster treatment times and better patient outcomes by prioritizing and escalating care more efficiently after diagnosis. Importantly, both this study and our project focus on integrating AI into existing workflows rather than replacing human decision-making, which underscores the importance of human-machine collaboration in healthcare.

(Batra et al., 2023)	The study asked whether AI-driven worklist reprioritization would measurably improve operational timeliness for CT pulmonary angiography (CTPA) cases that are positive for pulmonary embolism. Specifically, the authors examined whether promoting AI-positive exams to the top of the radiologist queue would reduce report turnaround time (RTAT) and pre-read waiting time, with attention to real clinical priority classes (stat, urgent, routine). The objective was pragmatic: evaluate if embedded AI that changes the queue, rather than merely flagging an exam, actually accelerates care-relevant steps for PE-positive imaging in daily practice.	A before–after implementation study in routine practice compared pre-AI and post-AI periods for adult CTPA exams. The team extracted RIS/PACS timestamps to compute RTAT and queue wait times, stratifying by exam priority class and operational hours. They then applied comparative statistics to test whether the AI's auto-promotion of PE-positive studies produced significant improvements. Importantly, the evaluation used real operational data rather than a simulation or reader study, allowing robust measurement of workflow outcomes that matter to patients (how quickly a flagged scan gets read) and to services (how queues behave under load). PubMed	AI auto-promotion reduced RTAT and queue waiting for PE-positive exams, with the biggest gains for routine-priority studies, the very cases that otherwise languished in first-in/first-out queues. Effects were less pronounced for stat/urgent exams (already high priority), underscoring that where AI affects the queue, it helps most. The actors (radiologists, coordinators) did not need extra clicks; the intervention worked because it changed default queue mechanics. Contextually, benefits depended on integration into PACS/RIS and real backlog dynamics, demonstrating that operational placement (not just model AUC) drives success.	For PMH outpatients, the lesson is to implement active worklist reprioritization, not just alert badges. Focus on routine outpatient CTs, where baseline priority is lowest and the marginal gain is greatest. Instrument dashboards for queue position, wait-time deltas, and RTAT as primary KPIs. Because improvements hinge on workflow integration, partner early with PACS/RIS admins to enable automatic promotion rules and audit trails. These design choices directly translate to faster attention for time-sensitive oncology complications discovered on outpatient CT, without adding clicks or cognitive load to radiologists.
(O'Neill et al., 2020)	The research examined whether active reprioritization of the radiology reading worklist, using AI for	The study employed quantitative methods, including three-way ANOVA and statistical modelling. Researchers analyzed	The study found that simply flagging or notifying radiologists of AI-detected ICH did not affect queue-adjusted wait times. However, active	This article provides crucial implementation guidance for our Princess Margaret Hospital project. It reveals that we shouldn't simply implement AI

	intracranial hemorrhage (ICH) detection on head CT, would reduce image wait times and report turnaround times compared to simple notification methods, such as widgets or flags.	scanner logs and electronic health records to extract workflow metrics. They compared three AI implementation approaches: notification with widget/flag only, versus active worklist reprioritization. The study controlled for factors such as patient location, examination order class (routine vs. urgent), and scan timing to isolate the effect of different AI presentation methods on wait times.	reprioritization, where AI-positive cases were automatically moved to the top of the reading queue, significantly reduced wait times from 15.45 minutes for negative cases to 12.02 minutes for positive cases. The impact was most significant for routine-ordered studies in both inpatient and outpatient settings, as these had the lowest baseline priority. This demonstrates that how AI results are presented to radiologists matters as much as the accuracy of detection. Passive alerts can be easily ignored or lost in busy workflows, whereas active queue reordering ensures that attention is drawn to critical findings.	detection, we need active worklist reprioritization where urgent findings automatically move to the top of radiologists' queues. The distinction between notification versus active reprioritization is critical for actual workflow improvement. For our outpatient CT prioritization system, we should design the interface so that scans flagged by AI are automatically promoted in the worklist, rather than just marked with an alert that may be missed or delayed by radiologists. The finding that routine-ordered scans benefit most reinforces our focus on outpatient imaging, which often begins with routine ordering despite the potential for critical findings. The study also emphasizes the importance of considering the broader workflow context, rather than just algorithm accuracy, when implementing AI tools.
(Ranschaert et al., 2021)	The research investigated how to optimize radiology workflow using artificial intelligence beyond image analysis, specifically	This was a comprehensive review article using qualitative synthesis methods. The authors analyzed existing literature	AI applications for workflow optimization show significant potential but face implementation challenges. Natural language processing,	This article broadens our understanding of where AI can benefit our Princess Margaret Hospital project beyond just prioritization algorithms. We

	examining AI applications for nondiagnostic tasks, including order entry support, patient scheduling, resource allocation, and improving radiologists' workflow efficiency.	and practical implementations of AI/machine learning in radiology operations. They examined various workflow optimization applications, including clinical decision support for exam ordering, automated protocoling, patient scheduling algorithms, and worklist management systems. The review synthesized findings from multiple institutions and discussed both technical approaches (machine learning, natural language processing) and operational considerations for implementing workflow AI.	combined with machine learning, can automate time-consuming tasks such as exam protocoling and help identify appropriate imaging protocols from clinical requisitions. Machine learning models can optimize patient scheduling by predicting exam duration and resource needs. The review emphasized that the accumulation of requisitions waiting to be protocolled contributes substantially to outpatient imaging wait times. Successful operational AI requires a robust data infrastructure, seamless integration with existing systems (EHR, RIS, PACS), and meticulous attention to local workflow patterns. The authors noted that operational AI tools remain less developed than diagnostic AI, despite potentially having a greater near-term impact on efficiency.	should consider the entire patient pathway, including how scans are ordered, scheduled, and protocolled, not just how they're prioritized for reading. For the outpatient CT workflow, automating protocol selection could reduce delays before scans are even performed. The emphasis on NLP for processing clinical indications is relevant, as our AI system will need to interpret ordering physician requests and patient histories. The article also emphasizes the importance of addressing infrastructure and integration requirements early in the planning process. We should ensure our prioritization system integrates seamlessly with Princess Margaret's existing RIS and PACS rather than operating as a standalone tool. The finding that protocoling backlogs contribute to outpatient delays suggests we might expand our project scope to include pre-scan workflow optimization in addition to post-scan prioritization.
(Yun et al., 2023)	The study aimed to develop and validate a deep	The researchers used deep learning methodology with a	The deep learning algorithm achieved AUCs of 0.77-0.80	While this study focuses on chest radiographs rather than CT scans,

	learning algorithm utilizing thoracic cage registration and subtraction techniques to automatically triage pairs of chest radiographs that show no change in longitudinal follow-up settings, particularly in emergency departments and intensive care units.	retrospective cohort design. They trained a convolutional neural network on 550,779 pairs of chest radiographs from 329,036 patients. The algorithm was validated on 1,620 pairs and tested on separate internal datasets from the emergency department (533 pairs) and ICU (600 pairs) settings. Performance was evaluated using area under the receiver operating characteristic curve (AUC), and specificity was assessed at different triage thresholds (40% and 60%). Ground truth was established by two thoracic radiologists reviewing randomly selected image pairs.	across validation and test sets. At a 40% triage threshold, the algorithm achieved approximately 90% specificity in both the ED and ICU settings, meaning it could correctly identify "no change" cases while maintaining sensitivity for detecting urgent findings, such as consolidation, pleural effusion, and pneumothorax. The algorithm's ability to automatically identify stable follow-up radiographs could significantly reduce radiologists' workload by allowing them to defer detailed review of unchanged images. The study demonstrated that AI can effectively handle longitudinal comparisons, not just single-timepoint interpretation, which is particularly valuable in settings where patients undergo frequent serial imaging.	it offers valuable insights for our Princess Margaret Hospital project regarding AI-assisted prioritization in cancer centers. Cancer patients often undergo serial imaging to monitor treatment response and disease progression. The concept of using AI to identify unchanged studies that can be triaged as lower priority is directly applicable to our outpatient CT workflow. In oncology settings with high volumes of surveillance imaging, an AI system that can identify stable follow-up scans would enable radiologists to focus their attention on cases showing interval changes or new findings. This could be particularly valuable for Princess Margaret Hospital's outpatient population undergoing routine surveillance imaging. However, we must ensure that the algorithm is carefully validated for oncology-specific contexts, where even subtle changes can be clinically significant.
(Annarumma et al., 2019)	The study wanted to develop and evaluate an automated machine learning-based triage system for adult chest	The researchers built a convolutional neural network (CNN)-based machine learning model trained to classify chest X-rays by	The AI-based triage system demonstrated potential to reduce reporting delays for critical chest X-ray findings from 11.2 days to 2.7 days. This was a	This study strongly supports the rationale behind our Princess Margaret project, demonstrating significant reductions in reporting delays through AI triage. The 75%

	radiographs that could prioritize studies based on urgency of imaging findings, hoping to reduce reporting delays for critical cases.	urgency level. They used quantitative methods to simulate the impact of automated triage on workflow efficiency. They analyzed reporting delay times and compared theoretical workflow scenarios with and without AI triage. The model was designed to automatically flag critical findings that need immediate radiologist attention and deprioritize normal or low-urgency studies.	75% reduction. This substantial improvement in turnaround time for urgent cases demonstrates the value of automated prioritization in settings with examination backlogs. The study showed that machine learning can effectively assess imaging urgency based on radiologic features, enabling intelligent worklist reordering. The magnitude of improvement was awe-inspiring for critical studies that would have been delayed in traditional first-in-first-out queuing systems. The research highlighted that automated triage addresses a fundamental workflow problem: the disconnect between clinical urgency and queue position in conventional radiology workflows.	reduction in time to report critical findings shows the real-world impact that automated prioritization can have on patient care. For our outpatient CT implementation, we should focus on the subset of scans most likely to have time-sensitive findings. The study validates that AI can bridge the gap between when urgent research is done and when it reaches the radiologist's attention. At Princess Margaret, where outpatient CT volumes are high and radiologists manage complex workloads, implementing similar automated triage could ensure cancer patients with critical findings - like complications, progression, or new metastases - get timely diagnosis and treatment planning. The study also emphasizes measuring actual workflow impact, not just algorithm accuracy.
(Bizzo et al., 2019)	The article examined how artificial intelligence can enhance clinical decision support (CDS) systems for both radiologists and ordering providers, focusing	This was a perspective article using qualitative analysis and synthesis methods. The authors reviewed existing CDS implementations in radiology and analyzed how	The article found that AI-enhanced CDS could significantly reduce friction in radiology workflows while improving patient safety and imaging appropriateness. For	This article demonstrates that our Princess Margaret AI prioritization should be viewed as part of a broader clinical decision support ecosystem, rather than a standalone tool. For our

	on opportunities to improve patient safety and drive value-based imaging through the synergy between AI and CDS.	AI technologies could enhance these systems. They examined CDS applications from two angles: radiologist point-of-care decision support and ordering provider decision support. The analysis included a discussion of how AI could enable more informed protocol selection, structured reporting, appropriate imaging utilization, and holistic patient-centred decision-making beyond just selecting imaging studies.	radiologists, AI can help with protocol selection, generate structured reports, and provide real-time guidance during interpretation. For ordering providers, AI-enabled CDS could evolve beyond simple imaging appropriateness criteria to consider patient-specific factors, previous imaging, and clinical context. The authors emphasized that CDS and AI form a 'virtuous cycle' where structured data from CDS fuels AI development, which in turn enables more sophisticated CDS. Successful implementation requires integration with existing clinical workflows and electronic health record systems. The article highlighted that AI's value in CDS goes beyond image interpretation to cover the entire diagnostic imaging pathway.	outpatient CT implementation, we should consider how the AI triage system integrates with other decision points in the imaging pathway, from order appropriateness through protocol selection to final interpretation and follow-up recommendations. The concept of AI reducing 'friction' in workflows is particularly relevant; our system should integrate seamlessly, allowing for automatic prioritization without requiring extra steps from radiologists or technologists. The article also suggests capturing structured data from our AI implementation to refine the system further and potentially develop additional CDS features. The emphasis on patient safety as a primary goal reinforces that our success metrics should focus on clinical outcomes - reduced time to treatment for urgent findings - not just workflow efficiency.
(Bhandari et al., 2024)	The article comprehensively reviewed how artificial intelligence is revolutionizing various aspects of radiology,	This was a comprehensive literature review using qualitative synthesis methodology. The authors reviewed recent publications	The review found that AI-powered triage systems are transforming radiology scheduling and worklist management by prioritizing	This review validates the multi-faceted approach we need for our Princess Margaret project. It confirms that AI triage for outpatient CT prioritization aligns

	including diagnostic accuracy, workflow efficiency, and patient care, with emphasis on practical applications across different radiological subspecialties.	and implementations of AI in radiology across multiple areas including machine learning, deep learning, and natural language processing applications. The review examined AI applications in image analysis, computer-aided diagnosis, workflow optimization (including triage and scheduling), radiation dose reduction, and clinical decision support. They analyzed evidence from clinical studies, implementation reports, and technical developments to assess AI's current state and future potential in radiology practice.	scans based on clinical urgency, ensuring that critical cases receive prompt attention. AI technologies have demonstrated significant potential to automate routine tasks, allowing radiologists to focus on complex diagnostic challenges. The article stressed that successful AI implementation requires addressing multiple challenges, including workflow integration, data quality, algorithm transparency, and clinician acceptance. The authors noted that while diagnostic AI applications get a lot of attention, operational AI tools for workflow optimization might offer more immediate practical benefits. Effective AI deployment requires multidisciplinary collaboration, strategic planning, and ongoing monitoring to ensure systems perform as intended in clinical environments.	with broader trends in radiological AI adoption and addresses a recognized clinical need. The article's emphasis on workflow efficiency improvements suggests our project could have substantial impact beyond just reducing interpretation delays - it could improve radiologist satisfaction and reduce burnout by helping them manage workload more effectively. The review's discussion of implementation challenges prepares us for obstacles we may face, including technical integration issues, the need for clinician training, and importance of ongoing performance monitoring. The article reinforces that we should design our system with user experience in mind, ensuring the AI triage tool integrates seamlessly into existing PACS workflows rather than creating additional steps. The emphasis on multidisciplinary collaboration suggests we should involve radiologists, IT staff, administrators, and potentially oncologists early in the design and implementation process.

(Savage et al., 2024)	This work asked whether, after department-wide deployment, AI triage for incidental PE (iPE) on contrast-enhanced chest or abdomen CT improves readers' sensitivity and/or changes report turnaround time. Unlike classic CTPA studies, this focuses on routine CECT where iPE is unexpected yet clinically urgent, mirroring oncology outpatients. The goal was to quantify real-world diagnostic performance and operational outcomes with AI assistance in the settings where iPE is most easily missed.	The team conducted a prospective clinical implementation evaluation comparing performance before vs. after AI deployment. They measured reader sensitivity for iPE and report TAT, using routine practice data across a broad CECT population. Because the study observed live departmental operations rather than controlled reader sessions, it captured how AI signals interact with everyday workload, scanner mix, and reporting habits, yielding pragmatic insight into effectiveness (not just efficacy)	Sensitivity for iPE increased with AI assistance, but report TAT did not significantly change. Actors (radiologists) benefited diagnostically, especially in contexts with low a priori suspicion, while the department's time metrics stayed flat without further process interventions. Contextual factors (notification pathways, staffing, competing priorities) constrained throughput gains. The lesson is that AI can enhance safety nets for subtle, unexpected findings, yet TAT improvements require change management (e.g., explicit escalation rules, protocolized follow-up).	For PMH, pair iPE detection with structured escalation (e.g., automated alerts to responsible clinicians or an internal "hotlist") and reader training to convert sensitivity gains into faster clinical actions. Because oncology outpatients frequently undergo routine CECT, incorporating an iPE triage signal into your outpatient CT prioritization ensures high-impact surprises don't wait in routine queues. Track sensitivity, near-misses, and downstream actions (anticoag start times) alongside TAT to capture patient-centred benefits.
(Hong et al., 2023)	The study wanted to comprehensively review all the challenges and limitations in developing and implementing AI in radiology, and discuss solutions beyond traditional supervised learning - including problems with data availability, model interpretability, and getting	The team conducted a prospective clinical implementation evaluation comparing performance before vs. after AI deployment. They measured reader sensitivity for iPE and report TAT, using routine practice data across a broad CECT population. Because the study observed live departmental operations	to address sociotechnical factors including clinician training, building trust, and change management.	This review helps us think ahead about challenges with our Princess Margaret CT triage system. The data heterogeneity issue is really relevant - we have to make sure our AI model is validated on Princess Margaret's specific CT protocols, patient demographics, and pathology mix, not just external datasets. The emphasis on model interpretability suggests we

	it to work in actual workflows.	rather than controlled reader sessions, it captured how AI signals interact with everyday workload, scanner mix, and reporting habits, yielding pragmatic insight into effectiveness (not just efficacy).		should add features that let radiologists see why the AI flagged a particular scan as urgent (like highlighting regions of interest or showing confidence scores). The federated learning discussion is relevant if we later want to improve the model using data from multiple institutions while respecting privacy. The attention to workflow integration challenges means we need to really understand Princess Margaret's current radiology workflow before designing our system. We should observe workflows and interview stakeholders to make sure our solution fits naturally into existing processes rather than forcing major changes. The article also emphasizes ongoing model monitoring and refinement after deployment to catch any performance drift.
(Rothenberg et al., 2023)	The authors investigated whether deploying an AI triage system for PE on CTPA improves real-world operational metrics and diagnostic performance. The core question: beyond accuracy on paper, does AI	This was a prospective evaluation comparing pre-AI and AI-assisted phases. The team collected operational timestamps and clinical performance measures across CTPAs, using a re-read reference standard and	AI improved wait times for PE-positive studies, meaning urgent cases rose to attention faster, but did not significantly change radiologist accuracy, miss rate, or report TAT. This reveals a common pattern: operational benefits arrive first;	For your PMH project, set primary success metrics around time-to-attention/queue position rather than immediately expecting TAT or accuracy gains. Ensure surfaced cases trigger clear escalation (e.g., smart notifications, secondary checks for

	triage shorten wait time to attention for PE-positive cases and improve accuracy or reduce miss rate once embedded in practice? The objective was to move from retrospective algorithm studies to a prospective, clinical assessment of what changes for patients and radiologists after implementation, including examination and report turnaround times.	predefined endpoints: wait time, accuracy, miss rate, and report TAT. By anchoring the analysis in routine workflow data and prospective scheduling, they could capture both queuing effects and reader behavior with AI present, providing a balanced view of technical vs. operational impact.	diagnostic or TAT improvements may lag without additional process changes. Actors include radiologists adapting to surfaced cases and coordinators managing queues; context includes load, staffing, and existing escalation pathways. The intervention's success depended on how AI output feeds the queue and notification channels, not solely on algorithmic detection quality..	high-risk patterns) so operational gains translate into time-to-treatment improvements. Build a shadow-mode phase to baseline wait times and then compare after activation. This study strengthens the case for operational instrumentation (dashboards, run charts) as part of governance and continuous monitoring.
(Brady et al., 2024)	This multi-society statement aimed to provide comprehensive guidance on the entire lifecycle of AI tools in radiology - from development and evaluation through purchasing, implementation, and ongoing monitoring - covering technical, clinical, business, and governance considerations.	This was a consensus statement developed collaboratively by five major international radiology societies (ACR, CAR, ESR, RANZCR, RSNA). The authors used expert consensus methodology, bringing together input from radiologists, informaticists, AI developers, and administrators from multiple countries. The statement covered the complete AI lifecycle including defining clinical needs and use cases, technical development considerations, clinical	The statement stressed that successful AI deployment needs attention to the entire product lifecycle, not just initial implementation. Key points include: AI products should address actual clinical needs rather than being tech solutions looking for problems; clinical validation has to go beyond just diagnostic accuracy to include workflow impact and real-world effectiveness; business considerations including total cost of ownership and demonstrating value are critical for sustainable adoption; integration challenges need	This authoritative guidance gives us a comprehensive framework and validates our approach of starting with the identified need for outpatient CT prioritization. The attention to total cost of ownership reminds us to think about not just acquisition costs but also ongoing expenses for maintenance, monitoring, and potential upgrades. The discussion of integration standards and interoperability challenges means we should prioritize solutions compatible with standard protocols (like DICOM, HL7 FHIR) to make integration with Princess Margaret's existing IT

		validation requirements, business and procurement evaluation, implementation and integration strategies, and post-deployment monitoring and governance. It incorporated perspectives from various stakeholders including end-users (radiologists), institutional buyers, AI developers, and regulators.	standardized protocols, and the current lack of standards creates big barriers; ongoing monitoring and governance structures are essential since AI performance can degrade over time due to changes in patient populations, imaging protocols, or equipment. Many AI failures come from not paying enough attention to human factors, including insufficient user training, poor interface design, and lack of stakeholder engagement during development. The societies emphasized the need for institutional AI governance committees to oversee AI portfolio management, monitor performance, and ensure patient safety.	infrastructure easier. The emphasis on governance structures suggests we should set up a clear oversight mechanism - maybe an AI steering committee with people from radiology, IT, administration, and quality/safety - to guide implementation and monitor performance over time. The focus on demonstrating value beyond just technical performance means we should plan to measure clinical outcomes (time to critical diagnosis, patient safety metrics) and operational benefits (radiologist satisfaction, workflow efficiency) to justify continued investment and support. The guidance reinforces that successful AI implementation is really an organizational change management challenge, not just a technical deployment.
(Yao et al., 2025)	The article evaluates how accurate a BERT Natural Language Processing model is at automatically triaging and protocolling CT and MRI requisitions.	They tested accuracy using quantitative methods. It was a retrospective study that analyzed 222,392 CT and MRI requisitions from 2018-2022. They trained a BERT model to automatically determine the urgency of each request and the appropriate protocol to	The BERT model performed really well at predicting both CT/MRI triage priority and protocol selection. It beat the traditional models, especially for rare cases. The model had high accuracy, correctly suggesting the right protocol in the top five options about 99% of the time,	The findings from this study validate that our project is feasible, demonstrating that NLP models, such as BERT, can accurately interpret requisitions and automate decision-making. It suggests good practices and protocols to consider when we're developing benchmarks for

		use. The data was split into training (80%), validation (10%), and test (10%) sets to check how well the model worked. They compared the model's performance with two other computer models (Naive Bayes and Support Vector Machine), measuring accuracy using F1 score, precision, and recall.	with the best results for emergency department requests. The study showed that a fine-tuned BERT NLP model can accurately automate radiology triage and protocol selection.	evaluating our system's accuracy and fairness. Validation metrics like F1 score and top-k accuracy are beneficial for what we're doing.
(Schmülling et al., 2021)	The researchers aimed to determine whether using deep learning to automatically detect pulmonary embolism (PE) on CT scans, combined with worklist prioritization and electronic notifications, would actually expedite the process in the emergency department, specifically by reducing communication times and increasing the speed of patient treatment.	They reviewed 1,808 CT pulmonary angiograms performed between April 2018 and June 2020. The study compared three different time periods: baseline (no AI), after the addition of the electronic notification system, and then after implementing the deep learning algorithm. They tracked factors such as the time it took radiologists to read reports, communication times, the time until patients received anticoagulation treatment, and overall patient turnaround times.	Honestly, this was disappointing - even though the AI was pretty accurate (82.2% PPV, 94.1% NPV), it didn't actually make things faster nine months after it was rolled out. None of the time metrics showed significant improvement. The key takeaway is that having good technology alone isn't enough. You need proper training, workflow integration, and staff buy-in. There's a real gap between having AI that works technically and actually seeing benefits in real clinical practice.	This study is a reality check for our project. We can't just assume that deploying a good algorithm will automatically improve things. We need to carefully consider how to integrate it into Princess Margaret's existing workflows, ensure that people are adequately trained, and gather feedback from users to refine the process. We should also be realistic about timelines - it might take longer than expected to see actual improvements. Change management will be just as important as the technical side.
(Maegerlein et al., 2019)	This study investigated whether AI could reliably	They employed a prospective design in which automated AI	The automated ASPECTS calculation worked well and was	This is particularly relevant for our project because it demonstrates

	calculate the Alberta Stroke Program Early CT Score (ASPECTS), which is used to assess stroke severity, and whether it would be as consistent as radiologists performing the calculation manually.	calculations were pitted against expert radiologists. Multiple people rated the same CT scans from stroke patients, and they measured the agreement between raters (inter-rater reliability) along with the usual performance metrics, such as sensitivity and specificity.	comparable to expert readers. The cool thing is it reduced the variability between different doctors' assessments, which is a known problem with manual scoring. The AI gave more consistent, objective scores. However, the authors emphasized that clinical judgment and context are still necessary for final decisions - the AI is intended to support doctors, not replace them.	that AI can provide standardized assessments that reduce inconsistency. We could develop urgency scoring systems that rank scans objectively based on what they show. The fact that they positioned AI as a support tool rather than the final decision-maker is the right approach for us too. Plus, aiming for consistent performance regardless of who's working or what time of day makes sense.
(Chilamkurthy et al., 2018)	This was a large study that aimed to develop and validate deep learning algorithms to identify several critical findings on head CT scans, including different types of brain bleeds, skull fractures, midline shift, and mass effect.	They went big with the data, collecting 313,318 head CT scans with reports from approximately 20 centers in India between 2011 and 2017. They split the data for training and validation, and then tested on a completely separate dataset (CQ500) from different centers. They measured sensitivity, specificity, ROC curves, and compared the AI's performance to actual radiologists.	The algorithms performed exceptionally well, with performance comparable to or even better than that of radiologists in detecting brain bleeds and fractures. They worked across different imaging centers and equipment, which is important. The study demonstrated that AI can identify time-sensitive problems that require urgent attention, which opens the door for automated triage. However, the authors emphasized the importance of proper validation, vigilance against bias, and ensuring its effectiveness across diverse patient populations.	This is the foundational study for what we're trying to do. It demonstrates that AI can detect multiple urgent findings simultaneously, which is precisely what a triage system requires. The multi-center validation approach is something we should follow when testing our system. It also reinforces why we're undertaking this project - to detect time-sensitive findings more quickly. We do need to be careful about the generalizability issues they mention and test across different patient groups and scanners.

(Prevedello et al., 2017)	They wanted to know if an AI system could automatically identify critical findings in imaging and send real-time alerts to doctors, thereby reducing delays in patient care.	They developed a natural language processing (NLP) system that reads radiology reports as they're being written and identifies critical findings. It was linked to the electronic health record, allowing it to notify the ordering doctors automatically. They tracked the accuracy, speed of notifications, and conducted user satisfaction surveys.	The system worked great - it accurately captured critical findings and was significantly faster than manual communication. The automated alerts were consistent no matter what time it was or how busy the radiologists were. It addressed the issue of relying on individuals to remember to report urgent findings, which is prone to human error and delays. Getting it integrated with the EHR was key to getting people actually to use it. Clinicians were happy with how fast and reliable it was.	This really drives home that prioritization alone isn't enough; we need to consider how urgent cases are communicated to radiologists and referring doctors. If scans get flagged but nobody notices or acts on it, what's the point? We should plan for seamless integration with Princess Margaret's existing systems (PACS, EHR, etc.) rather than creating a standalone solution. Additionally, incorporating backup systems and audit mechanisms into the workflow is sensible.
(Choi et al., 2024)	This study looked at how a deep learning algorithm for detecting brain bleeds affected ER doctors' decision-making in a simulated environment. They wanted to see if it actually changed how doctors diagnosed cases and made clinical decisions.	Ten ER doctors from a tertiary hospital reviewed CT scans twice - first without AI assistance, then with the algorithm's input. It was a simulation study that measured changes in their diagnostic accuracy (sensitivity, specificity, etc.) and looked at whether their decisions became more consistent using kappa statistics. They also tested the algorithm on 2,146 real CT scans from their hospital.	The algorithm demonstrated decent but not exceptional performance, with 70.81% sensitivity and 86.72% specificity. Interestingly, it didn't significantly benefit experienced doctors, but it was valuable for less experienced clinicians. The impact depends on who's using it - it acts as a safety net for junior staff but doesn't add much value for senior experts. This suggests it's most useful in situations where experienced personnel are unavailable, such	This is particularly relevant for considering who our system will benefit most. We should design it to be especially useful for less experienced readers and provide off-hours coverage when senior radiologists are unavailable. When evaluating it, we should separate the results by experience level to see the real impact. The moderate performance also reminds us to be transparent about limitations and ensure that doctors know when to trust versus question the AI's recommendations.

			as night shifts or understaffed hospitals.	
(Zech et al., 2018)	This was an essential reality-check study that tested whether deep learning models trained at one hospital to detect pneumonia on chest X-rays would still work well when applied to images from other hospitals. Does the AI generalize or just memorize hospital-specific quirks?	They trained CNN models on chest X-rays from multiple hospitals and then carefully tested performance on data from the same hospital versus different hospitals. They investigated the reasons behind the performance drop, examining differences in patient populations, equipment, and image processing. They used Grad-CAM visualizations to see what the models were actually learning.	The results were concerning - performance dropped significantly when applied to external datasets, even for a straightforward task such as pneumonia detection. The models often learned hospital-specific things (like how images were processed or how patients were positioned) instead of actual disease features. This 'shortcut learning' meant models that looked great on internal testing failed in the real world. It effectively highlighted the challenges of deploying AI across various clinical settings.	This is a must-read cautionary tale for our project. We cannot assume that our algorithm will work well simply because it performs well on our development data. We need to validate across diverse sources, including different CT scanners, protocols, and possibly other hospitals if possible. Our evaluation plan needs to test for generalization and catch potential confounders specifically. We should also plan for ongoing monitoring after deployment to catch any performance issues. We need diverse, representative training data from the start.
(Hugh et al., 2023)	To develop and validate a machine learning model that classifies musculoskeletal radiograph requisitions as appropriate/inappropriate based on clinical guidelines	Quantitative methods - retrospective study using 50 000 musculoskeletal radiograph (labeled) requisition datasets and trained ML classifiers (specifically random forests and support vector machines). The trained	Out of 50 000 requisitions, 12 253 (24.5%) were deemed to contain an inappropriate indication. A Naive Bayes model correctly classified requisitions with an accuracy of 98%.The ML model accurately classified requisition appropriateness,	Ambiguous and limited data will likely be the biggest hurdle tha the model we develop will face. Analyzing requisition appropriateness is feasible, but accuracy in special cases needs special considerations

		models were then evaluated based on accuracy, sensitivity and specificity	showing potential in standardizing ordering practices. The model struggled with borderline and complex cases. There were instances of misclassifications, due to incomplete clinical data and ambiguous requisitions.	
(Büyüktoka et al., 2025)	The researchers aimed to create and test a locally adapted BERT-based LLM that would automatically score radiology requisitions based on standardized criteria.	An LLM was applied to requisition text extracted from the Reason for exam Imaging Reporting and Data System (RI-RADS), and compared with the standards set by human expert scoring criteria.	The model achieved a strong agreement with human raters, in terms of assessing text quality of clinical documents.	Meaningful clinical data can be extracted from free-text requisitions.
(Liu et al., 2025)	To determine whether the quality of radiology requisitions, assessed using the RI-RADS (Radiology Requisition Appropriateness and Diagnostic Score) system, reflects the underlying clinical reasoning in emergency CT referrals	The study evaluated emergency CT referrals using the RI-RADS framework, which scores requisitions based on completeness, clarity, and clinical relevance. Researchers retrospectively analyzed CT requisition forms from emergency patients and correlated RI-RADS scores with diagnostic outcomes and appropriateness.	When CT scan requests were clearer and more complete, they had more accurate RAD scores; good-quality requisitions tend to show that the doctor had strong clinical reasoning behind ordering the scan. There was high variation in the quality of requisitions.	Retrospective studies/data are good at informing the correlation between clinical reasoning and requisition quality, but are also a limitation because there could be bias in the scores given for each requisition assessed. Having means to mitigate the potential bias that could exist in criteria development is also necessary and important as we establish ground truth.
(Tekcan Sanli et al., 2025)	To test ChatGPT's ability to classify BI-RADS categories	The study used quantitative methods; using 352 breast	ChatGPT demonstrated moderate agreement with the	Commercial models like ChatGPT can accurately interpret

	from narrative based breast MRI reports. More specifically, they wanted to know if ChatGPT could correctly guess the BI-RADS category (2, 3, 4a, 4b, 4c, or 5) based just on the descriptions of the findings, and also to check if it could tell benign cases (BI-RADS 2-3) from suspicious or malignant ones (BI-RADS 4-5).	MRI reports from one center collected between Jan 2024-June 2025, an appropriate date was selected. Each report that met the criteria was given to ChatGPT to classify as benign/malginant and then with two questions: what the BI_RADS category should be, and what the next clinical step should be. Expert breast radiologists reviewed ChatGPT's answers to agree on the accuracy of the results	radiologists consensus. The accuracy was highest for extreme (i.e,. BIRADS 5 category) reports, but there was lower agreement on intermediate categories. In the binary classification of data to be benign or malignant, ChatGPT had almost perfect agreement. Most notably, the model's management recommendations (i.e, what the next step is) were 100% consistent with the BI-RADS categories.	unstructured breast MRI reports, especially in benign/malignant discrimination. This emphasizes the need to have granular and specific classifications for accurate categorization of data. Also, while technology holds potential to standardize reporting and enhance clinical workflows, especially in settings with variable reporting practices, prospective, multi-institutional studies are needed for further validation. Categorizing imaging based on a pre-existing system (P1-P4 in our case) may prove useful for informing/guiding standards when developing criteria, but it may not serve the user (i.e, PFCs) if used in this context.
(Wee et al., 2024)	This article aimed to draft position statements from an Asian working group of AI users (mostly clinical radiologists) regarding the application and clinical deployment of AI in radiology, addressing why AI adoption has been slow	This was a consensus-based position paper developed by a working group of clinical radiologists and AI users from various Asian countries including India, Japan, Malaysia, Singapore, Taiwan, Thailand, and Uzbekistan. The group discussed and drafted position statements based on their collective	AI is gaining recognition in radiology and more radiologists are becoming AI-literate, but actual adoption and implementation in clinical settings has been super slow with lots of points of disagreement. The working group identified several key issues: need for validation in diverse populations and	This position paper from practicing radiologists across different countries gives us a reality check about implementation challenges. The emphasis on validation in diverse settings reminds us that we can't just assume our system will work equally well for all patient populations at Princess Margaret. The discussion of infrastructure

	despite growing recognition.	experiences with AI implementation in different healthcare settings across Asia.	healthcare systems, importance of addressing data privacy and security concerns (especially with different regulations across countries), challenges with integration into existing infrastructure, and the need for appropriate training and education for radiologists. The article emphasized that context matters - what works in one healthcare system or country might not work in another due to differences in resources, regulations, patient populations, and workflows.	challenges and integration issues highlights that we need early conversations with IT about technical requirements and compatibility with existing systems. The point about training and education means we should plan for comprehensive training programs, not just a quick tutorial. The article also suggests we should anticipate resistance and skepticism from some radiologists and plan for how to address concerns.
(Cellina et al., 2022)	The article aimed to examine AI applications, specifically in emergency radiology, by investigating how AI can aid in the rapid diagnosis and management of various emergencies, as speed is literally a matter of life or death in this context.	This comprehensive review examined AI applications in emergency radiology. The authors examined the use of AI across the emergency radiology workflow, from image acquisition and quality optimization to automated detection of various emergency conditions and workflow integration. They reviewed studies on AI for detecting intracranial hemorrhage, bone fractures, pneumonia, and other emergencies.	AI has numerous potential applications in emergency radiology, and they're instrumental because speed is critical. For image acquisition, AI can assist with automatic positioning and reduce artifacts to optimize image quality, even for critical patients. For workflow, AI algorithms can analyze patient characteristics and images to detect high-priority exams and patients with urgent critical findings. Several studies have shown that AI-based triage tools can	Although this focuses on emergency radiology, and our project is about outpatient CTs, the principles are remarkably similar - both involve using AI to identify urgent cases that require faster attention. The emphasis on workflow integration with PACS is crucial for us too. The examples of significant reductions in turnaround time (like the 44% decrease) give us benchmarks for what kind of improvements we should be aiming for. The article also reminds us that in clinical settings, AI needs to handle

			significantly reduce the turnaround time for critical findings. For example, one study demonstrated a 44% decrease in turnaround time for abnormal chest X-rays. The automated detection of conditions such as intracranial hemorrhage, fractures, and acute abdominal emergencies can help radiologists identify relevant findings more quickly. However, the review noted that integration with existing RIS-PACS workflows is essential for these tools actually to work in practice.	imperfect conditions - such as non-ideal patient positioning and artifacts - so we should test our system on messy, real-world data, not just perfect examples.
(Bruno et al., 2025)	This article documents discussions from the 2024 Intersociety Summer Conference regarding AI's impact on radiology, with a focus on current challenges with AI integration, regulatory gaps, and the observed slow adoption by radiologists.	This was a conference summary documenting discussions from a meeting held in August 2024 in Boston, with 60 attendees, including executive committee members, invited faculty, and leaders from 27 societies across radiology subspecialties, such as imaging, interventional radiology, radiation oncology, and medical physics. The meeting aimed to clarify the current state of AI, develop a	There's an expectation that AI will have a massive impact on radiology, with big potential benefits but also significant risks. However, actual adoption has been slow. Key discussion topics included: lack of effective use cases in some areas (like radiation oncology screening planning scans for incidental findings), regulatory and liability concerns (like who's responsible if AI misses something or if charging for AI-assisted interpretation creates	This conference summary reveals that even experts and societal leaders are grappling with how to implement AI in practice effectively. The discussion about liability is particularly relevant - we need to think about legal and regulatory implications of our triage system. What happens if our AI misses an urgent finding or incorrectly flags a routine scan as urgent? How does this affect radiologist liability? The mention of infrastructure gaps reinforces that we cannot simply build a

		shared understanding of integration challenges, and address regulatory and infrastructure issues.	malpractice liability), infrastructure and integration gaps, and general challenges around implementation. The meeting participants recognized that, while there's a lot of hype around AI, real-world integration faces practical barriers that need to be addressed systematically.	model and assume it'll work; we need proper technical infrastructure and integration. The slow adoption issue suggests we plan for skepticism and resistance, and focus on demonstrating clear value to overcome it.
(Chong et al., 2024)	This article aims to propose a standardized framework for implementing machine learning in clinical radiology practice, addressing why there has been so little actual benefit from AI in hospital settings despite recent advancements.	This review article analyzed recent literature and empirical evidence from radiologic imaging applications. The authors proposed a framework focusing on three key components: problem identification, stakeholder alignment, and pipeline integration. They examined what has worked and what hasn't in AI implementation efforts across various hospital practices.	Despite the progress in machine learning for healthcare, there have been few tangible benefits or improvements to clinical medicine in hospitals yet. The authors identified three critical components needed for successful implementation: first, you need to clearly identify the actual clinical problem you're trying to solve; second, you need to get all stakeholders (radiologists, IT, and admin) aligned and on board; and third, you need to integrate the AI smoothly into existing clinical pipelines. The framework emphasizes that technical performance of the AI model isn't enough - you need organizational readiness, workflow integration, and	This framework is super helpful in planning our Princess Margaret project. It reinforces that we need to start by clearly defining the problem (reducing delays for urgent outpatient CT findings) rather than just implementing cool AI technology. The emphasis on stakeholder alignment means we should involve radiologists, booking staff, IT, and oncologists from the very beginning to get buy-in. The pipeline integration component suggests that we map out the entire current workflow and determine precisely where and how our AI triage system will fit in without disrupting the rest of the process. The article's central message, that technical success doesn't equal clinical success, is something we need to keep front and center.

			ongoing stakeholder engagement.	
(Choy et al., 2018)	The article aimed to review the current and future applications of machine learning in radiology, examining interpretive and non-interpretive uses, while discussing what ML can and cannot do in clinical practice.	This comprehensive review article, published by Massachusetts General Hospital, examined the current state and future potential of machine learning in radiology. The authors reviewed literature on ML applications across different radiological tasks, including image interpretation, workflow optimization, and operational applications. They analyzed the gap between ML's technical capabilities and actual clinical implementation.	ML has shown promise in radiology for both interpretation-based systems (detecting abnormalities, diagnosing conditions) and non-interpretive applications (workflow optimization, operational efficiency). For interpretation, ML systems have been developed to identify life-threatening abnormalities, such as intracranial hemorrhage; however, these are primarily used for prioritizing studies on worklists rather than making final diagnostic decisions. Several studies have shown that ML can improve interpretation when used as an aid to radiologists. However, for ML to function as an independent interpreter, extensive data-derived knowledge is required, and simple detection doesn't account for clinical context - such as how free air in the abdomen is normal after surgery but critical otherwise. The authors emphasized that ML is more realistically positioned	This review helps frame our project realistically - we're building a prioritization tool, not a diagnostic system, which is the right approach. The emphasis on ML as an assistant rather than a replacement aligns with how we should position our system to radiologists. The example about clinical context (free air being normal post-op but critical otherwise) reminds us that our triage system might need to consider clinical history and context, not just imaging findings alone. For Princess Margaret oncology patients, knowing whether they have recently undergone surgery or treatment is crucial for correctly prioritizing findings. The article also reinforces that we should focus on the use case where ML is most ready, workflow optimization and triage, rather than attempting to perform full diagnostic interpretation.

			as a tool to assist radiologists rather than replace them.	
(Gichoya et al., 2022)	This study investigated whether standard AI deep learning models can detect race from medical images across multiple imaging modalities, and if so, what the implications are for fairness and bias in AI applications.	The researchers utilized both private datasets (Emory CXR, Chest CT, Cervical Spine, Mammogram) and public datasets (MIMIC-CXR, CheXpert, National Lung Cancer Screening Trial, RSNA Pulmonary Embolism CT) to investigate whether deep learning models could accurately predict race from medical images. They evaluated performance across multiple imaging modalities, assessed whether anatomic features or other confounders explained the models' ability to detect race, and investigated the underlying mechanism.	This study found something concerning - standard AI models can be trained to predict race from medical images with high accuracy across multiple imaging types (X-ray AUC 0.91-0.99, CT chest 0.87-0.96, mammography 0.81). This detection isn't due to obvious proxies, such as BMI, disease distribution, or other covariates they tested. Even more worrying, the models' ability to detect race persisted across all anatomical regions and frequency spectrums of the images, indicating that it's embedded in the images in complex ways. This suggests that efforts to remove or control this behaviour when it is undesirable will be particularly challenging and require further study. The finding raises serious concerns about potential bias in AI applications.	This study is a major wake-up call for our project. Although we're building a triage system based on clinical findings, we must be particularly cautious about potential racial bias. We should test our system's performance across different racial and ethnic groups in Princess Margaret's patient population to make sure it doesn't prioritize or deprioritize cases differently based on race. We need to implement fairness checks and monitoring throughout development and after deployment. The article suggests that this is a challenging problem to solve, so we should be transparent about its limitations and monitor for any disparate impacts. We should also consider having diverse representation in our training data.
(Mello-Thoms & Mello, 2023)	The article aimed to explore the clinical applications of AI in radiology, examining both interpretive uses (such	This was a comprehensive review that looked at published literature on AI applications in radiology. The	AI can be used to triage patients by identifying exams that are more likely to have critical findings and putting them at the	This article is particularly relevant for considering how our Princess Margaret prioritization system should function. The example of

	as aiding in diagnosis) and non-interpretive uses (including workflow management), while also discussing the factors hindering AI adoption in actual clinical practice.	authors examined evidence for various AI use cases in clinical practice and analyzed the barriers to their adoption. They specifically searched for studies on AI in clinical practice and found that although tons of articles discuss AI in radiology (over 2,000), only about 2% actually talk about real clinical implementation or trials.	top of the radiologist's reading list. One example they cited showed a machine learning model for intracranial hemorrhage that flagged 94 out of 347 routine cases as emergencies, with 60 being true positives and 34 being false positives. It detected five new hemorrhages and cut reporting time from 8.5 hours down to just 19 minutes. However, a practical question arose: how should AI prioritize studies if they originate from different imaging types and body parts? Should a head CT with brain bleed be prioritized above or below a chest X-ray with pneumothorax? There's no clear answer yet. The article also pointed out that, despite all the hype, the actual clinical implementation of AI in radiology remains relatively limited.	cutting reporting time from 8.5 hours to 19 minutes for critical cases is precisely the kind of impact we're hoping for. However, the question of how to prioritize across different findings is something we'll need to figure out. If our system flags multiple urgent cases, we'll need clear criteria for determining which one gets seen first. The finding that there's a vast gap between AI research and actual clinical implementation is a warning that we need to focus on practical deployment from the start, not just building a model that works in theory.
(Ngiam & Khor, 2019)	This is review paper that explores the landscape of big data and how it can improve healthcare delivery in oncology.	This study did a literature review on ML and big data applications across various healthcare domains, including areas like diagnostic accuracy, prognostic	The paper highlights that ML models generally have superior performance than current traditional methods in areas of diagnosis, prognosis and risk stratification	Active clinician engagement was key for implementing the triage system in hospital environments, It would be helpful to understand how administrative feedback could mitigate some of the challenges seen when it comes to

		modeling and healthcare operations.	Challenges highlighted include how the heterogeneity of data and complexity of the preprocessing process make integration and interpreting ML models difficult. There are additional ethical concerns around patient privacy, data security and building clinician trust which influences successful adoption of many tools.	integration of the administrative side of clinical workflows.
(Farzaneh et al., 2025)	The paper asked whether a multicenter, multivendor deep learning model can reliably detect incidental PE on routine contrast-enhanced CT (non-CTPA), a scenario crucial for oncology surveillance, while maintaining generalizability across sites and scanners. The objective was to validate an iPE detector that extends beyond PE-protocol studies to the scans where iPE is often discovered late, enabling prioritization and faster	A multicenter, multivendor retrospective validation across diverse institutions and hardware tested a standalone deep learning model on routine CECT. The authors reported diagnostic performance and emphasized generalization across scanners/vendors. The open-access design provides transparency on data sources and evaluation, aligning with best practices for external validity and deployment suitability in heterogeneous environments like large cancer centers.	Findings support robust generalization to non-PE-protocol CTs, reinforcing feasibility for broad screening/triage in routine oncology imaging. Because iPE prevalence is low yet outcome-critical, an automated detector that consistently flags positives across sites and vendors is valuable. Success hinges on seamless integration (PACS/RIS), confidence display, and alert tuning to avoid fatigue. The paper underscores that cross-site validation and ongoing monitoring are essential to sustain performance under	For PMH's outpatient CT, this supports adding an iPE detection service into the pipeline to auto-surface urgent, unexpected events across varied scanners. Use site-specific validation and post-deployment monitoring to track drift. Combine with active worklist reprioritization so flagged outpatient studies jump the queue. This strengthens your governance plan: standardized metrics, shadow mode → pilot, and equity monitoring for any systematic performance gaps across patient subgroups or scanner types.

	action in real-world mixed workflows.		evolving patient populations and scanner upgrades.	

Table 2: Statement of Key Findings

Emerging themes from literature reviewed	Provide 3 themes from the literature (common findings across studies, key ideas/conclusions that you found, or major controversies that you uncovered). **Use in-text citations when referring to articles.** 1. AI Must Be Designed for Integration Within Real-World Clinical and Administrative Workflows a. A consistent finding across the literature is that AI tools only succeed when they align closely with existing clinical workflows and institutional processes, beyond just technical accuracy. For example, Hallinan et al. (2025) showed that an institutional large language model improved MRI protocol adherence by fitting seamlessly into established workflows. Similarly, Büyüktoka et al. (2025) demonstrated that large language models (LLMs) could reliably score requisition quality when integrated into radiology processes. Conversely, AI tools that ignore real-world workflow complexities, such as interdepartmental communication or scheduling logistics, face adoption challenges, as noted by Jing et al. (2025). This aligns with broader findings from other studies emphasizing the importance of human–AI collaboration and system integration (Knight et al., 2023; Paudyal et al., 2023). Tools that ignore these realities risk poor adoption despite technical promise (Cellina et al., 2022; Wee et al., 2024). 2. Stakeholder Trust, Transparency, and Buy-in Are Prerequisites for Adoption a. AI tool success hinges on how much users, particularly clinicians and administrative staff, trust and understand the system. In Din et al. (2025), clinicians expressed optimism about AI but raised concerns about explainability, error tolerance, and transparency. Similarly, Paudyal et al. (2023) observed that technical excellence in tasks like segmentation didn't translate to clinical use due to workflow misalignment and lack of stakeholder confidence. Even in non-AI interventions like Al Harbi et al. (2024) and Szekeres et al. (2025), strong stakeholder engagement (through PDSA cycles and shared planning) was a key success factor. Additionally, Knight et al. (2023) recommend that AI implementation must be framed around institutional goals such as reducing wait times or improving provider satisfaction to gain traction. Additionally, proactively addressing legal and privacy concerns, as discussed by Kohli et al., (2024) are key actions that will build confidence and compliance. 3. Prioritization Is a Valuable Lever, but Requires Standardization and System-Level Awareness b. Several studies caution against viewing AI as a silver bullet, as improvements in one area often cause new pressures elsewhere. For example, Szekeres et al. (2025) significantly reduced CT scheduling delays through workflow and capacity changes, but saw no improvement in appointment start delays and a rise in report

	turnaround times, indicating the creation of new downstream bottlenecks. Similarly, Knight et al. (2023) note that AI scheduling tools often optimize one part of the system while neglecting the interdependencies like radiologist availability or transport logistics. The CADTH (2023) review also makes clear that improving access requires combining technology with structural changes in intake, referral, and prioritization processes. Prioritization emerged as a central lever across nearly all interventions. However, its effectiveness depends on standardized definitions and clinical context, such that system interdependencies can be considered, or else effectiveness will be limited. Standardization does not only consider clinical context, but other factors including fairness monitoring against racial bias and granular data backed by standardized criteria can ensure accurate and equitable prioritization.
Research /Knowledge gap	Overall takeaways for your project. What direction do you think the project needs to go in after reviewing the literature? **Use in-text citations when referring to articles.** Overall, the current literature on AI applications in CT scanning primarily concentrates on diagnostic interpretation in radiology or data classification using the imaging data itself, with limited attention to leveraging requisition forms or referral information to optimize scheduling and prioritization. Knowing this better informs the impact this project can have; it has the potential to address this critical gap by focusing on the analysis of requisition data, which could significantly improve patient triage and resource allocation at Princess Margaret Cancer Centre (Chen et al., 2022; Zhang et al., 2024). Moving forward, the project should develop an AI model that accurately predicts urgency and optimizes scheduling based on referral content, ensuring transparency and explainability to build clinician trust (Knight et al., 2023). Integrating this system into existing workflows with continuous feedback from clinicians and staff will be essential for adoption and sustained impact. By doing so, the project not only stands to enhance operational efficiency and patient outcomes locally but also contribute valuable insights to a largely unexplored research area, expanding the scope of AI in medical imaging beyond diagnostics (Szekeres et al., 2025).

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