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CADTH Horizon Scan

Artificial Intelligence for Patient Flow

Key Messages

Why Is This an issue?

- Inefficient patient flow contributes to the overcrowding of health care settings and negative clinical outcomes and patient experiences downstream.
- Patient flow management aims to achieve seamless patient movement through the health care system and between acute and long-term settings, ensuring timely access to quality care.

What Is the Technology?

- Artificial intelligence (AI)-based patient flow management tools are interventions designed to forecast and monitor patient movement from admission to discharge as they progress through different care settings. AI-driven tools can leverage big data and digital information systems (e.g., electronic health records) to facilitate effective patient flow.
- AI-based patient appointment scheduling tools, which can help improve patient flow, are created to automate appointment scheduling and optimize it by minimizing wait times and matching the demand for health services and hospital capacity.

What Is the Potential Impact?

- AI tools for patient flow management can support volume forecasting of patients with various conditions, especially those experiencing chronic conditions that require different types of treatment or care in different settings over a long period of time.
- These AI tools can predict admissions, patient movement from the emergency department to inpatient beds, discharge, and transfers to different health care settings. Evidence for their effectiveness in patients with emergency admissions and those transferred to tertiary and quaternary care, as well as inpatients from the general, cardiology, and mental health departments, was reported. In addition, evidence suggested that AI tools can optimize appointment scheduling in general outpatient settings and operating rooms.
- In health care systems in Canada, AI tools are being used or investigated to enhance patient flow by predicting emergency admissions, transfers to alternate levels of care, and general inpatient discharges, as well as optimizing capacity planning for patients receiving oncology care. AI appointment scheduling tools are currently being used in some oncology care settings and operating rooms across Canada.

Key Messages

- The implementation of AI systems generally requires an upfront investment of time and other resources in addition to the financial cost of the system itself for set-up, integration, and staff training. The goal of these systems is to improve efficiency and save money, time, and human resources in the long run.

What Else Do We Need to Know?

- Patient privacy and data security issues are concerns regarding widespread implementation of AI tools trained on electronic health records systems and patient datasets.
- AI algorithms trained on datasets lacking adequate representation of all relevant patients may not predict their flow accurately. Training datasets with sufficient data from all relevant patient groups can ensure the inputs and outputs of the algorithms accurately reflect patient care needs and mitigate potential bias.
- To accurately predict the care needs of local patients, AI algorithms, once deployed, should be retrained on site-specific datasets containing data for the patient populations that are representative of the hospital or health system in which they are being used.
- Not all institutions have the hardware or computing power available to adequately or efficiently process the large amounts of data that are required by these AI systems, or the infrastructure needed to use big data (e.g., from electronic health records), and may require additional resources for implementation, as well as for ongoing maintenance and updating of the systems.

Purpose and Scope

The purpose of this horizon scan is to present health care stakeholders in Canada with an overview of information related to the use of artificial intelligence (AI), such as machine learning (ML), which is a subset of AI, to improve the flow of patients within, and between, health care settings. This report also provides examples of how these technologies are being used within health care systems in Canada.

Studies that modelled patient flow without providing any real-world use cases were not included in this review. This report is not a systematic review and does not involve critical appraisal or include a detailed summary of study findings. It is not intended to provide recommendations for or against the use of AI for patient flow.

Background: Why This? Why Now?

Health care settings are busy and often overcrowded. Backlogs and overcrowding in health care settings have become a larger and more consistent problem since the beginning of the COVID-19 pandemic. Manually scheduling appointments, people, tests, treatments, treatment spaces, and patient transfers takes time and can be a complex task that requires the coordination of multiple resources. It can be difficult to track a patient's movement through the health care system and between acute and long-term settings. Modern health systems typically have large amounts of data and digital information systems (e.g., electronic health records, digital imaging results) that can be leveraged by using AI to optimize patient movement.

The Technology: What Is It? How Does It Work?

Patient flow is a term used within health care to refer to the way patients are moved through the health care system. It includes all parts of the system and the human and physical resources required to move a patient from admission, through treatment, to discharge to the community or another health care setting.[1] The quality of service and patient satisfaction are ideally maintained throughout the process.[2] Patient flow forecasting is a methodological approach to predict and monitor the movement of patients over time and through various stages of their treatment and care.[3] The prediction of patient flow can be broken up into 4 sections: prediction of emergency department (ED) demand and admissions, prediction of patient flow from the ED to inpatient care, prediction of patient movement within the hospital, and prediction of length of stay.[1] This forecasting method is often used for people experiencing chronic conditions (e.g., Alzheimer disease, traumatic brain injury, cystic fibrosis) who require treatment or management over a long period of time and who might need different types of acute and long-term care in different care settings over that time.[3]

AI can be used to improve patient flow:

- within a single health care setting (e.g., triaging patients in the ED, identifying people who should be moved from the ED to inpatient beds, predicting time to discharge)

- between health care settings (e.g., estimating time to discharge or transfer to another care setting, such as rehabilitation or long-term care).

Instead of the currently used manual methods of planning and tracking patient flow, AI algorithms use data (e.g., patient age, diagnosis, vital signs, average length of treatment, clinical history) that can be drawn directly from electronic health records to predict patient outcomes. Those predictions inform patient flow forecasting and resource planning with an aim to maximize efficiency and quality of care while minimizing disruption to patient flow.[1,3] Emergencies and unplanned admissions cause the most disruption to patient flow. Patients admitted after an emergency tend to have more unpredictable treatment needs and recovery times compared to more routine patients, like those admitted for a planned surgical procedure.[1] AI systems are able to more accurately predict the resource needs and health status of people admitted for emergencies and unplanned admissions, which allows for more precise inputs to patient flow models.

Automation and optimization in patient appointment scheduling can also be considered a relevant technology in this space. AI-informed scheduling can help improve wait times and overall efficiency so patients get access to the care they need more quickly. One of the current issues slowing patient flow is the unavailability of services in the settings that can provide the appropriate type of care for patients to be transferred to.

> **AI systems can help predict when patients will be ready for discharge or transfer and schedule appointments accordingly, which allows for more effective allocation of staff time and attention to the patients who need it most.[1]**

Place in Care: How Could This Change Care?

The use of AI to manage patient flow could be beneficial to both patients and health care providers. Finding efficiencies in patient flow and automating and optimizing patient appointment scheduling can save time and resources across health care systems. For example, AI tools that collect real-time patient flow data from hospital departments can reschedule resources using a synchronization mechanism, which maximizes efficiency.[4] The ability to accurately track and move a patient with a chronic condition through the various phases of care they may require could result in increased patient satisfaction, as well as more accurate information for their health care providers to inform their care. For instance, AI discharge prediction tools can reduce discharge delays, a common issue that causes inefficient patient flow, by identifying patients ready for discharge and their potential discharge barriers.[5] This information could be shared directly and daily with health care providers through existing communication systems so they could prioritize these patients' discharge activities and proactively investigate discharge challenges,[5] thereby improving patient satisfaction and optimizing bed capacity.

Regulatory Status

AI systems that do not meet the definition of medical devices by Health Canada, such as patient flow and appointment scheduling tools, are not under regulatory oversight in Canada.[6] In the context of medical devices, Health Canada, the US FDA, and the UK Medicines and Healthcare Products Regulatory Agency jointly released 10 guiding principles for the development of ML-enabled medical devices in 2021.[7] The intended use and risk categorization of each ML-enabled medical device will determine which, if any, regulatory requirements it may need to meet to be authorized for use in health care. The use of in-house–developed AI tools or adaptations of free AI software may fall within a regulatory grey area. These principles acknowledge the growing role that AI will play in health care going forward.

Examples From Canada

A summary of examples of AI interventions being used in Canada to manage patient flow or appointment scheduling are provided in Table 1. These examples were identified through the grey and published literature searches for this project. The identified AI interventions for patient flow were mostly classified as in development for use at hospitals or health care centres in Ontario and Quebec in EDs, oncology units, or discharge to the community or alternate levels of care. The 3 AI systems for appointment scheduling that were identified are currently in use in Montreal and Toronto. Due to the dynamic nature and rapid changes of AI research and development, other implementations of AI systems for patient flow and appointment scheduling are likely to exist.

Table 1: Examples From Canada of AI and ML for Patient Flow or Appointment Scheduling

Developer and site (publication year)	Stage of development or use	Description of technology
AI interventions for patient flow		
Humber River Health Apotex ED, Toronto, ON (2024)[8]	In development	• This intervention is an AI-enabled virtual queue management application. • It includes a patient-facing app and a staff-facing dashboard. • The intervention could improve patient flow by advising the patient before they arrive whether they should come to the ED immediately, come at a scheduled time later in the day, visit with a physician or nurse practitioner online, or go back to their primary care provider. • The rationale for implementation is to provide patients the opportunity to wait at home more comfortably than be on standby in the ED for an unspecified time. A controlled flow of patients is also expected to reduce stress on ED physicians and staff, enabling them to focus on critical cases. • The intervention will be implemented and studied by the research institute over the next 2 to 2.5 years.

Developer and site (publication year)	Stage of development or use	Description of technology
Grand River Hospital, Waterloo, ON (2023)[5] Trillium Health Partners, Toronto, ON (2023)[9]	In use	• This intervention is an AI tool created by Signal 1 and named Discharge Predictor. • The tool uses an ML model based on common EMR data to identify patients who are approaching clinical stability and who should be prioritized for discharge assessment to streamline the hospital discharge process.
Hospitals in ON and QC (2023)[10]	In development	• This intervention aims to develop, deploy, and evaluate AI software to address challenges in patient flow, capacity planning, and coordination of service delivery for oncology patients. • The various sites will incorporate a range of ML and statistical modelling approaches to determine the ideal resources required to sustain patient flow.
Chuang et al. (2022),[11,12] ON	In development (using 13 years of historical patient data)	• This intervention uses AI to improve discharge planning. • It predicts the health status of patients, usually older adults, and the associated cost of their transitions to different parts of the health care system, including ALC. • It uses AI to determine which patient would benefit more from an available bed rather than using a first come, first served approach and can also provide individuals who are at risk with earlier access to community resources.
AI interventions for appointment scheduling		
Centre hospitalier de l'Université de Montréal, Montreal, QC (2023)[13]	In use	• This intervention provides automated and optimized scheduling of appointments for patients with cancer. • The hospital reported that the intervention led to a 5% increase in efficiency at the infusion clinic, resulting in 11 hours of extra treatment capacity per day and an 80% decrease in administrative burden.
McGill University Health Centre, Montreal, QC (2023)[13]	In use	• This intervention is a predictive and prescriptive decision support tool for central OR booking and surgery scheduling. • The health centre reported that the optimization of joint OR scheduling identified opportunities to perform additional surgeries. The prediction of postsurgical bed availability supports discharge planning.
Princess Margaret Cancer Centre (UHN), Toronto, ON (2023)[13]	In use	• This is an AI-automated radiotherapy scheduling platform that prioritizes patient appointments based on severity of disease and incorporates patient preference into appointment timing. • The cancer centre reported that the intervention resulted in a 13% decrease in mortality rate from delayed access to radiotherapy and that the reduction in scheduling time allowed care coordinators to spend more time on patient support and more complex tasks.

AI = artificial intelligence; ALC = alternate level of care; ED = emergency department; EMR = electronic medical record; ML = machine learning; ON = Ontario; OR = operating room; QC = Quebec; UHN = University Health Network.

Cost and Administration

No information was identified that outlined the costs of specific AI systems for patient flow or appointment scheduling, including the AI tools listed in Table 1.

The implementation of AI systems will require resources for set-up, integration, and staff training. With that, there is the presumption of an upfront investment of time and other resources in addition to the financial cost of the system itself. The goal of these systems is to improve efficiency and save money, time, and human resources in the long run.

What Is the Evidence?

Patient Flow Within a Single Care Setting

We identified 2 narrative reviews[1,14] and 2 retrospective studies[15,16] investigating AI-powered tools that support patient flow management within a single care setting. Further details of these reviews and studies are available in Table 2 in Appendix 2. These tools used patient-level data, such as demographics, previous health care usage, and medical history, to improve the accuracy of their predictions.[15] The AI tools were developed for various patient populations, including inpatients from the general,[16] cardiology,[15] psychiatric,[14] and ED units.[1] As none of the studies were conducted in Canada, the generalizability to current clinical settings in Canada is unclear.

The authors reported that these AI tools were effective at forecasting the volume of patients by predicting:

- emergency, elective, and inpatient admissions from the ED[1]
- movement of inpatients (e.g., ward transfer)[1]
- patient readiness for discharge[1,16]
- readmissions after discharge.[1,14]

The authors reported that these AI tools were also effective at supporting resource planning and management by predicting:

- inpatient resource use (e.g., CT scan, laboratory testing)[1]
- hospital length of stay.[15]

The authors of 1 narrative review concluded that predicting ED admissions and readiness for discharge was more effective at improving patient flow than predicting movement of inpatients, such as ward transfer.[1] This was because patients were generally admitted to the appropriate ward from the outset.[1]

Patient Flow Between Care Settings

One retrospective study found that an AI model could predict the transfer of inpatients to tertiary and quaternary care as accurately as current human workflow, while also identifying significantly more tertiary and quaternary cases than humans could.[17] Further details of the study are available in Table 2 in Appendix 2.

The authors of the study concluded that integrating the AI model into the existing electronic health record workflow could enhance efficiency by automating and improving tertiary and quaternary care case identification and prioritizing these cases in the early transfer process for admission and bed management.[17] However, the model was developed in a US academic health centre without external validation; therefore, the generalizability of the model to other health care systems is unclear.[17]

Appointment Scheduling

In addition to admission and transfer prediction, AI applications can support patient volume forecasting through appointment scheduling automation and optimization. Specifically, AI models can maximize scheduling efficiency by:

- predicting the probability of patients attending their scheduled appointments[18]
- assigning patients with high predicted no-show probabilities into an overbooked time slot to improve health service utilization.[18]

We identified 1 systematic review investigating the use of AI patient appointment scheduling models in real-world settings, which included 9 studies in outpatient settings and 1 study in an inpatient setting (i.e., operating room).[18] Further details of the review are available in Table 3 in Appendix 2. The authors of the review concluded that these models can decrease the burden on provider time, increase patient satisfaction, and ultimately provide more patient-centred health care and efficiency.[18] However, the number of real-world studies identified was limited, and none of the primary studies were conducted in Canada, which may limit the generalizability of the findings.[18]

Perspectives and Experiences

Dawoodbhoy and colleagues (2021),[19] academic researchers from the UK, investigated AI and mental health experts' perspectives of AI for patient flow in acute mental health units for inpatient. The study participants expressed that AI may enhance patient flow by managing administrative tasks, such as patient record keeping, improving resource allocation, and bed capacity management through accurate prediction of demand.[19]

> The use of automation of data extraction from electronic health records as part of the AI-embedding process may also reduce some of the administrative burden on the health care provider and provide them with more time to spend with patients.[19]

A research team in Canada, Upshaw et al. (2023),[20] explored the perspectives of patients, providers, and health system leaders living in Canada regarding AI applications in primary care. Participants in the study were asked what use cases of AI applications they thought should be prioritized in primary care settings in Canada. Health care providers and health system leaders reported that AI applications that support practice operations, including those that predict surges in visits to direct resource planning, should be highly prioritized.[20] The majority of participants in the study indicated their belief that AI tools in health care should be applied in ways that work to reduce inequities in the system. Application of AI to areas that currently contribute to provider burnout or limit access to care were also identified as priorities by the participants. The participants also highlighted the need for continuing education for health care providers in basic AI literacy, algorithm critical appraisal, and workflow integration.[20]

Additional Considerations

Karim Lekadir and colleagues (2022),[2] representing a panel for the European parliament, outlined 7 categories of risks and challenges of AI in health care that were identified from the literature. The list included:

- patient harm due to AI
- misuse of medical AI tools
- risk of bias in medical AI and perpetuation of inequities
- lack of transparency
- privacy and security issues
- gaps in AI accountability
- obstacles to implementation in real-world health care.

Some of the issues associated with the use of AI in health care in general are discussed next.

Considerations for Implementation and Generalizability

Datasets

Researchers who have investigated the use of AI tools in health care have identified the need for common datasets that all researchers can use to train their AI, benchmark their models, and test against.[1] There is also a need to come to consensus on definitions for different patient characteristics (e.g., how old is "elderly"?) and patient groups. Although the concept of having large, common datasets available for researchers to use is a good one, questions remain about how well researchers can maintain patient anonymity and data safety. There is also a lack of standardization in how patient data are collected between health care institutions and in different health care settings, which introduces the potential for inconsistency and gaps in the available data.[1]

Data Security, Hardware, and Software

Even anonymized data can be reverse engineered to identify the patient if the right data remains in the patient record. Electronic health records contain large amounts of unstructured data; these clinical notations and other unstructured data make it difficult to fully anonymize electronic health records data.[19]

Some institutions do not have the hardware or computing power available to adequately or efficiently process the large amounts of data that are required by these AI systems.[19] Some health care systems, like the National Health Service in the UK, have tried and failed to implement these types of AI systems, which resulted in costs to the health care system with no return.[19] AI systems will require maintenance and updating even after they have become an established part of a health care institution's workflow.

Inclusion, Diversity, Equity, and Accessibility

In addition to informing patient flow and appointment scheduling, AI can be used to assist health care providers with identifying potential diagnoses based on reported symptoms, interpreting medical imaging results, and predicting the health outcomes of patients based on current symptoms and their medical history. None of the information provided by AI can be used in isolation.

> **When using AI to aid in patient diagnosis or treatment decisions, the analytical thinking of the health care providers needs to be combined with the computational power of computers to incorporate the AI data into a patient's care plan in a contextually appropriate way.**

AI algorithms can only learn from the information available in the dataset they were trained on. This reliance on the quality and quantity of the training dataset makes AI algorithms prone to bias (e.g., if the dataset does not accurately represent the true population, if inequities exist in the dataset that can result in substandard outcomes for the population).[21] Men who are middle aged and white are the most represented group within the datasets that have so far been used to train AI tools. Health-related data for groups like women who are Black, Indigenous people, people with disabilities, and people living in rural and remote areas are less likely to have been proportionately included in the training datasets. The inclusion of communities that are underrepresented in existing health datasets in the design of AI tools can help ensure the inputs and outputs of the algorithms accurately reflect their reality and needs. These communities can help to identify specific biases and gaps in the existing information that relate to themselves.[21]

The development of AI-specific ethical frameworks could facilitate safer and more consistent development of AI tools in health care by preventing the misuse of AI technologies and minimizing the spread of misinformation.[22,23]

In terms of patient flow and discharge planning, AI systems should be retrained with data relevant to the patient populations that are representative of the hospital or health system they are being used within to mitigate any biases or incorrect assumptions about the population that are inherent to the original training dataset.[16] The prevalence of different diseases and conditions can vary greatly depending on the geographical location and population demographics of those seeking care at a particular health care centre. For example, the prevalence of type 2 diabetes can vary from 3.5% to more than 20% in different populations.[1] These kinds of differences will influence the accuracy of an AI algorithm when applied to each group. Researchers have suggested that AI-based discharge planning systems should be used by hospital bed managers and administrators to place distance between the clinician and the algorithm to avoid biasing their clinical decision-making based on the algorithm's predictions for the patient.[16]

Shanklin and colleagues (2022),[24] a group of academic researchers from the US, found that AI scheduling algorithms were more likely to assign patients who were Black to overbooked time slots because the algorithm associated them with lower predicted clinical attendance probabilities based on historical data than patients who were not Black in the US. The biased algorithms can lead to longer wait times for patients who historically have challenges accessing health services, which reinforces health inequities.[24] The study explored different approaches to reduce the risk of racial bias.[24] The authors found that a race-aware algorithm can maintain schedule quality (i.e., decrease overall patient wait time, provider downtime, and provider overtime) while minimizing the risk of inequitable access.[24] Rather than reducing wait time for the general patient population, the race-aware algorithm focused on wait time reduction for patients belonging to the racial group expected to wait longer. However, the race-aware AI scheduling algorithm was not evaluated in people living in Canada; therefore, its generalizability to health systems in Canada was unknown.

Future Developments

The landscape of AI algorithms and technologies in health care is ever evolving. In Canada, the adoption of AI in health care is still in the early phases with room for growth. The results of a survey conducted in 2022 showed that more than 77% of the health care organizations in Canada surveyed had an AI strategy in place.[25] Academic hospitals and health agencies are establishing AI partnerships and in-house AI development.[25] Future developments could further build off of the data and digital systems already in place in health care settings, such as electronic health records and digital imaging files.[1] Wearable sensors for vital sign monitoring could be used to help increase the prediction accuracy for patients being admitted to the hospital from the ED or to improve the accuracy of discharge predictions from the hospital to a patient's home or other health care setting.[1] More information about wearable devices for vital sign monitoring can be found in this CADTH report Single-Use Wearable Wireless Sensors for Vital Sign Monitoring, published in November 2023.

Final Remarks

AI-based patient flow management tools are designed to predict and monitor patient movements (e.g., patient admission, transfer, and discharge) through the health care system and between acute and long-term settings. These tools can be supported by additional AI tools for appointment scheduling and informing decision-making on optimizing hospital capacity and resource allocation to meet patient needs. The evidence to support the effectiveness of AI systems for patient flow to change clinical outcomes and patient experiences is unclear, especially in Canada, although the authors of the publications included in this report presented favourable immediate outcomes, such as effective patient volume forecasting and the ability to support resource planning and management. Improving patient flow will also mean sending more patients to individual providers. This increase in patient volume will need to happen alongside a reduction in paperwork and other demands (e.g., complex care delivery) that providers might be faced with, which may also be addressed using AI algorithms and tools.

The use of AI tools to inform patient flow and appointment scheduling is still in the early phases of implementation. Implementing AI tools may require upfront investment of various resources, such as time and financial costs for system set-up, integration into existing systems, maintenance, and staff training.

> Concerns persist regarding the preservation of patient privacy and the security of data when using existing accessible AI systems that are trained on electronic health records and patient datasets.

These concerns might need to be weighed against the risks of not using AI and not benefiting from its use in health care systems. Some health care institutions in Canada are in the early stages of testing these systems and many more are in development. More research and testing may be required before these systems are ready for widespread implementation. The use of AI systems within health care settings should be considered as a support to humans and their expertise, not as a replacement for them.

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Appendix 1: Methods

Note that this appendix has not been copy-edited.

Literature Search Strategy

An information specialist conducted a literature search on key resources including MEDLINE, Embase, the Cochrane Database of Systematic Reviews, Scopus, the International HTA Database, the websites of Canadian and major international health technology agencies, as well as a focused internet search. The search approach was customized to retrieve a limited set of results, balancing comprehensiveness with relevancy. The search strategy comprised both controlled vocabulary, such as the National Library of Medicine's MeSH (Medical Subject Headings), and keywords. Search concepts were developed based on the elements of the research questions and selection criteria. The main search concept was AI or ML and patient flow. The search was completed on January 30, 2024, and limited to English-language documents published since January 1, 2019.

Study Selection

Two authors screened the literature search results and reviewed the full text of all potentially relevant publications. Publications were considered for inclusion if the intervention was an AI or ML intervention to manage patient flow or for appointment scheduling. Conference abstracts and grey literature were included when they provided additional information to that available in the included publications.

Appendix 2: Characteristics of Included Publications

Note that this appendix has not been copy-edited.

Table 2: Studies and Reviews of AI Patient Flow Management Tools

Author, Year, Country	Topic Area, Study/Review Design	Population, AI Model, Comparator, Outcomes	Main Findings

Abuhay et al. (2023)[15]
Ethiopia
	Patient flow within a single care setting
	Retrospective study
		• Patient population
		  ◦ Cardiology inpatients
		• Patient flow model
		  ◦ ML based LoS prediction model
		• Comparator
		  ◦ Poisson distribution based LoS prediction model
		• Performance outcomes of LoS prediction models
		  ◦ Mean absolute error
		  ◦ Accuracy
			• Mean absolute error in ML model vs. Poisson distribution model: 0.0035 vs. 0.002
			• Accuracy of the ML model (NR for the Poisson distribution model): 76%
			• The model was developed in a single site without external validation.

Lee et al. (2023)[17]
US
	Patient flow between care settings
	Retrospective study
		• Patient population
		  ◦ General inpatients transferred to TQ care
		• Patient flow model
		  ◦ NLP based TQ case prediction model
		• Comparator
		  ◦ Transfer centre human workflow predictions of TQ cases
		• Performance outcomes of TQ case prediction
		  ◦ Accuracy
		  ◦ Sensitivity
			• NLP model vs. human prediction of TQ cases:
			  ◦ Accuracy: 81.5% vs. 80.3% ($P = 0.198$)
			  ◦ Sensitivity: 83.6% vs. 67.7% ($P < 0.001$)
			• The model was developed in a single site without external validation.

Bishop et al. (2023)[16]
UK
	Patient flow within a single care setting
	Retrospective study
		• Patient population
		  ◦ General inpatients
		• Patient flow model
		  ◦ ML based next-day discharge readiness prediction model
		• Comparator
		  ◦ NA
		• Performance outcomes, for the top 20% patients with the highest discharge readiness probability scores
		  ◦ PPV
		  ◦ NPV
			• PPV and NPV were high for patients on their first day of but dropped for patients further into a longer admission.
			• First day of admission
			  ◦ PPV = 0.96 for planned admissions, 0.94 for emergency admissions
			  ◦ NPV = 0.98 for planned admissions, 0.93 for emergency admissions
			• Seventh day of admission
			  ◦ PPV = 0.66 for planned admissions, 0.71 for emergency admissions
			  ◦ NPV = 0.73 for planned

Author, Year, Country	Topic Area, Study/Review Design	Population, AI Model, Comparator, Outcomes	Main Findings
			admissions, 0.75 for emergency admissions • The model was developed in a single site without external validation.

Cecula et al. (2021)[14]
UK
	Patient flow within a single care setting
	Narrative review
		• Patient population
		  ◦ Mental health inpatients
		• Patient flow models
		  ◦ ML models predicting ED admissions, ED to inpatient admissions, inpatient ward transfers, and discharges
		• Comparator
		  ◦ NA
		• Performance outcomes of relevant models
		  ◦ NR
			• AI can be used in patient flow management to predict avoidable readmissions, improve care efficiency, optimize resource allocation, and reduce LoS.
			• The use of AI in psychiatric health care remains largely unexplored. Important aspects such as the patient's experience, clinical significance, and ethical considerations require further studies and evaluation.

El-Bouri et al. (2021)[1]
UK
	Patient flow within a single care setting
	Narrative review
		• Patient population
		  ◦ Patients with planned or emergency admissions
		• Patient flow models
		  ◦ ML models for patient flow
		• Comparator
		  ◦ NA
		• Performance outcomes
		  ◦ NR
			• ML prediction models can help address patient flow problems by predicting the demand on a health care institution, the demand and resource required to transfer patients from the ED to the hospital, potential resources required for the treatment and movement of inpatients, and LoS and discharge timing.
			• A shared dataset was essential for researchers to benchmark their algorithms, enabling future studies to build upon current research.
			• ML for the improvement of patient flow was a new field with very few publications reporting appropriate ML methods for the problem being considered.

AI = artificial intelligence; LoS = length of stay; ML = machine learning; NA = not applicable; NLP = natural language processing; NPV = negative predictive value; NR = not reported; PPV = positive predictive value; TQ = tertiary and quaternary.

Table 3: Systematic Review of AI Patient Appointment Scheduling Tools

Author, Year, Country	Topic Area	Type of Review, Number of Included Studies, AI Model, Comparator, Outcomes	Main Findings
Knight et al. (2023)[18] **US**	Patient flow within a single care setting	• Systematic review • 11 studies ◦ Outpatient setting: n = 10	• Available evidence shows heterogeneity in the stages of AI development as they

Author, Year, Country	Topic Area	Type of Review, Number of Included Studies, AI Model, Comparator, Outcomes	Main Findings
		◦ Inpatient setting (i.e., operating room): n = 1 • AI Model ◦ NR • Comparator ◦ NR • Outcomes ◦ Missed appointment outcomes: patient double-booking volume, missed appointments, service use, and missed appointment risk ◦ Resource allocation outcomes: wait time, disease-type matching performance, schedule efficiency revenue, and new patient volume wait time. ◦ Other outcomes: visit requests, examination length prediction, and surgical case time	apply to patient scheduling. • AI applications can be used to decrease the burden on provider time, increase patient satisfaction, and ultimately provide more patient-directed health care and efficiency for medical practices. • No *black-box* neural network models were reported. It is not clear whether *black-box* networks reduced accuracy for these tasks or whether explainable models were highly valued for these use cases.

AI = artificial intelligence; NR = not reported.

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